Analysis and Detection of Driver Fatigue Caused by Sleep Deprivation

by

Ji Hyun Yang

Submitted to the Department of Aeronautics and Astronautics
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY IN AERONAUTICS AND ASTRONAUTICS
at The
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
September 2007

Author ______________________________________
Department of Aeronautics and Astronautics
September 2007

Certified by ______________________________________
Eric Feron
Visiting Professor, Department of Aeronautics and Astronautics
Professor, School of Aerospace Engineering, Georgia Institute of Technology
Thesis Supervisor

Certified by ______________________________________
Joseph Coughlin
Senior Lecturer, Engineering Systems Division
Thesis Supervisor

Certified by ______________________________________
Zhi-Hong Mao
Assistant Professor, Department of Electrical and Computer Engineering, University of Pittsburgh
Thesis Advisor

Certified by ______________________________________
Lee Yang
Charles Stark Draper Laboratory
Thesis Advisor

Accepted by ______________________________________
David L. Darmofal
Associate Professor, Department of Aeronautics and Astronautics
Chair, Committee on Graduate Students

Analysis and Detection of Driver Fatigue Caused by Sleep Deprivation

by

Ji Hyun Yang

Submitted to the Department of Aeronautics and Astronautics
on September 2007, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy in Aeronautics and Astronautics

Abstract

Human errors in attention and vigilance are among the most common causes of transportation accidents. Thus, effective countermeasures are crucial for enhancing road safety. By pursuing a practical and reliable design of an Active Safety system which aims to predict and avoid road accidents, we identify the characteristics of drowsy driving and devise a systematic way to infer the state of driver alertness based on driver-vehicle data. Although sleep and fatigue are major causes of impaired driving, neither effective regulations nor acceptable countermeasures are available yet.

The first part of this thesis analyzes driver-vehicle systems with discrete sleep-deprivation levels, and reveals differences in the performance characteristics of drivers. Inspired by the human sleep-wake cycle mechanism and attributes of driver-vehicle systems, we design and perform human-in-the-loop experiments in a test bed built with STISIM Drive, an interactive fixed-based driving simulator. In the simulated driving, participants were given various driving tasks and secondary tasks for both non and partially sleep-deprived conditions. This experiment demonstrates that sleep deprivation has a greater effect on rule-based tasks than on skill-based tasks; when drivers are sleep-deprived, their performance of responding to unexpected disturbances degrades while they are robust enough to continue such routine driving tasks as straight lane tracking, following a lead vehicle, lane changes, etc.

In the second part of the thesis we present both qualitative and quantitative guidelines for designing drowsy driver detection systems in a probabilistic framework based on the Bayesian network paradigm and experimental data. We consider two major causes of sleep, i.e., sleep debt and circadian rhythm, in the framework with various driver-vehicle parameters, and also address temporal aspects of drowsiness and individual differences of subjects. The thesis concludes that detection of drowsy driving based on driver-vehicle data is a feasible but difficult problem which has diverse issues to be addressed; the ultimate challenge lies in the human operator.

Thesis Supervisor: Eric Feron
Title: Visiting Professor, Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Professor, School of Aerospace Engineering, Georgia Institute of Technology

Thesis Supervisor: Joseph Coughlin
Title: Senior Lecturer, Engineering Systems Division

Acknowledgments

I specially thank Prof. Eric Feron, who has been my sincere advisor ever since I first came to MIT. He has been a constant source of inspiration and encouragement. His enthusiasm and unique perspective have motivated myself continuously. For the past two years, he consistently supported me despite of a geographical challenge in remote advising.

I would like to express my gratitude to Dr. Joseph Coughlin, who has provided critical advice and enormous support. He has understood my situations, given endless words of encouragements, and provided insightful feedbacks on my research.

I would like to acknowledge the constant support from Prof. Zhi-Hong Mao, who provided critical ideas on my doctoral research. His solid background on Neuroscience helped me to interact with diverse research areas. He continuously encouraged me so that I could keep my positive attitude. I was very grateful that he flew from Pittsburgh to Cambridge to join my defense. I would like to thank Dr. Lee Yang, who has not only been a committee member, but has been a great mentor ever since I came to MIT. His brilliant advice and words of encouragement helped me to survive the MIT life.

I am grateful to Dr. Tom Pilutti and Prof. Emilio Frazzoli for their advices which led to significant advances in my research. In particular, I would like to thank to Tom for sharing his brilliant ideas and supporting my experiments while I stayed at Ford Motor Company in 2005. I would like to thank to Emilio for his interests and timely advices for my research. It is an honor for me to thank Prof. Greitzer for his critical questions and kindness.

It is my pleasure to thank Active Safety Group at Ford Motor Company. They provided me an enormous support and many suggestions for my experiments. I am thankful to Jeff Rupp and Mike Shulman for giving me the opportunity to work with the Active Safety Group. I had many discussions with Louis Tijerina and Dev Kochhar, and their advices were very critical to set up my experiment. I am grateful to Rebecca Seiler for her brilliant advising and kindness. I am thankful to Peter Joh for his willingness to help me on my research. Thank you, Reid Steiger, Jim Martell, Tom Boettcher, Muhammad Siddqui, Dave Winnard and Jerry Engelman. I also would like to thank the VIRTTEX group. Discussions with Jeff Greenberg and Ksenia Kozak were very helpful for me to design my experiment. I am grateful to Reates Curry, Larry Cathey, Mike Blommer, and Buce Artz for sharing their areas of expertise.

Dr. Chris Drake from Henry Ford Hospital and Ted Rosenthal from Systems Technology Inc. deserve credit for their contributions on the experimental design and STI programming. I am thankful to all experimental subjects who voluntarily participated in my experiment.

My MIT life cannot be defined without other students and lab mates. The Feron-lab was huge, and I was able to meet smart people from all over the world. Undoubtedly, the friendly and brilliant colleagues enriched my life at MIT. Thank you, Ioannis Martinos, Jan De Mot, Vlad Gavrilets, Tom Schouwenaars, Masha Ishutkina, Rodin Lyasoff, Farmey Joseph, Jerom Le Ny, Mardavij Roosbehani, Animesh Chakravarthy, Glenn Tournier, Mario Valenti, and Emily Craparo. Of course, without consistent help from Lisa Gaumond, Engela Copyak, and Lauren Clark, nothing in the lab would function smoothly. I am so grateful to Emily Craparo and Eric Jones for their smart advices and kindness. I cannot thank enough to Marie Stuppard and Barbara Lechner for their understanding and support. My last year at MIT was with AgeLab. It was my pleasure to be around them. I specially thank to Michelle Pratt for her critical advice and kindness. Thank you, Bryan Reimer, Lisa D'ambrosio, Jonathon Long, Vincent Lammers, Anna Pohlmeyer, and Alex Narvaez. I am grateful to Paula Magliozzi, Karen van Nederpelt, Nancy Martin, and Chris Caplice for their support and kind encouragement.

It was my pleasure to meet many other Korean students at MIT. I am grateful to Jhohngwoo Peck and SoonJo Chung for sharing agony of MIT life. Thank you, Sang-il Lee, Hanlim Choi, Hyung-il Ahn, Jinho Jang, Mina Jun, Do-Nyun Kim, Jun-geun Park, SeungBum Hong, and Tairin Hahn.

My MIT life would have been very un-balanced without ballet and tennis. I specially cannot forget ballet nights with Wonseon Choi. I am also grateful to the members of Boston3040 Tennis club. I had lots of fun playing doubles.

I cannot be here without my parents endless, unconditional support and love. Dad has always encouraged my professional carrier. Mom came to my defense, and I was so happy. I am also very thankful for her special care when I had morning sickness a few weeks before the defense. I dedicate this thesis to them. I miss my sister and brother so much. Finally, I would like to thank my dear husband, Chandeok Park, who made me smile in any occasions. He has been incredibly patient, understanding, and encouraging. At the same time, he has been a critical reviewer of my research.

This work is funded by Ford/MIT Alliance Program, US Department of Transportation, and New England University Transportation Center whose support is gratefully acknowledged.

Contents

List of Figures

List of Tables

Nomenclature

Roman

$1(\cdot)$	Unit step function
a	Distance from front wheels to center of gravity
B	Backlash
b	Distance from rear wheels to center of gravity
$C_{\alpha f}$	Front cornering stiffness
$C_{\alpha r}$	Rear cornering stiffness
c	Constant in Backlash model
d	Effect size index
F	False
F_{aero}	Equivalent longitudinal aerodynamic drag
F_x	Longitudinal tire force
H_0	Null hypothesis
H_1	Alternative hypothesis
I_z	Polar moment of inertia
K	Gain in the Crossover model
m	Slope in Backlash model or Vehicle mass
N	Sample size
n	Number of data within sampling window
$P(\cdot)$	Probability
p	Statistical significance
R_x	Force due to rolling resistance

T	True
t_0	Initial time in sampling window
t_f	Terminal time in sampling window
U	Longitudinal velocity
v	Lateral velocity
$x(k)$	Driver's lateral lane position with respect to the centerline of driving lane
Y_H	Transfer function of human
Y_P	Transfer function of plant

Greek

α	Threshold value in RMT or Type I error
β	Type II error
δ	Steering wheel angle
θ	Lapse threshold or Angle of inclination of the road
ρ	Spearman's correlation coefficient
τ	Effective time delay
$\dot{\psi}$	Yaw rate

Acronyms

ABS	Antilock Braking System
ACWAS	Automotive Collision Warning and Avoidance System
APVT	Auditory Psychomotor Vigilance Task
BAC	Blood Alcohol Content of Blood Alcohol Concentration
CL	Curved Lane Tracking
CRR	Correct Response Rate
DLCT	Double Lane Change Task
DUI	Driving Under the Influence
EEG	Electroencephalography
EM	Emergency Maneuver
EOG	Electrooculogram
ESS	Epworth Sleepiness Scale
ETL	Effective Time Delay
FA	False Alarm
fMRI	Functional Magnetic Resonance Imaging
HOS	Hours of Service
IVHS	Intelligent Vehicle Highway Systems
KSS	Karolinska Sleepiness Scale
LDW	Lane Departure Warning System
LR	Lapse Rate
LT	Straight Lane Tracking
LV	Straight Lane Tracking given a Lead Vehicle
MEG	Magnetoencephalography
NREM	Non-Rapid Eye Movement
NTP	Network Time Protocol
PERCLOS	Percentage Eye Closure
REM	Rapid Eye Movement
REX	Rate of Exceedance
RMS	Root Mean Square Error

RMT	Root Mean Square Error with Threshold
ROC	Receiver Operating Characteristic
RSC	Roll Stability Control System
RT	Reaction Time or Response Time
SA	Successful Alert
SC	Straight Lane Tracking given Changes of Steering Dynamics
SCN	Suprachiasmatic Nucleus
SLCT	Single Lane Change Task
SOC	System Operating Characteristic
SSS	Stanford Sleepiness Scale
STD	Standard Deviation
SWWR	Steering Wheel Reversal Rate
VPVT	Visual Psychomotor Vigilance Task
WG	Straight Lane Tracking given Wind Gusts

DOT	U.S. Department of Transportation
FHWA	Federal Highway Administration
ITS	Intelligent Transportation Systems
NASA	National Aeronautics and Space Administration
NCSDR	National Center on Sleep Disorders Research
NSF	National Sleep Foundation
NTSB	National Transportation Safety Board
NHTSA	National Highway Traffic Safety Administration

Chapter 1

Introduction

In the past decades, there has been worldwide interest in the analysis and management of fatigue-related transportation accidents, and significant efforts have been devoted to its study. On-line driver monitoring devices in motor vehicles have received renewed attention for managing fatigue in the U.S.A. and Europe since the late 1990's.

Among all fatigue-related accidents, crashes caused by fall-alseep-drivers are common and serious in terms of injury severity. As these lines are being written, countless people are driving while fatigued or drowsy. Despite the wide-spread occurrence of drowsy driving and the risk it generates, no nationwide regulations exist for drowsy driving as they do for driving under the influence. Subjective estimates of sleepiness are unreliable, and there is a strong perceived need for objective drowsiness-detection technologies.

1.1 Motivation

Until recently, most safety-related research has focused on methods to reduce damage caused by transportation accidents while they are occurring and after they happen. Front/side air bags attempt to alleviate injuries in the case of an automobile collision. Crash dummy tests analyze data to mitigate the effects of motor vehicle accidents on human bodies. These are called *Passive* Safety features, because they do not actively prevent accidents from occurring. They deal with situations on the assumption that

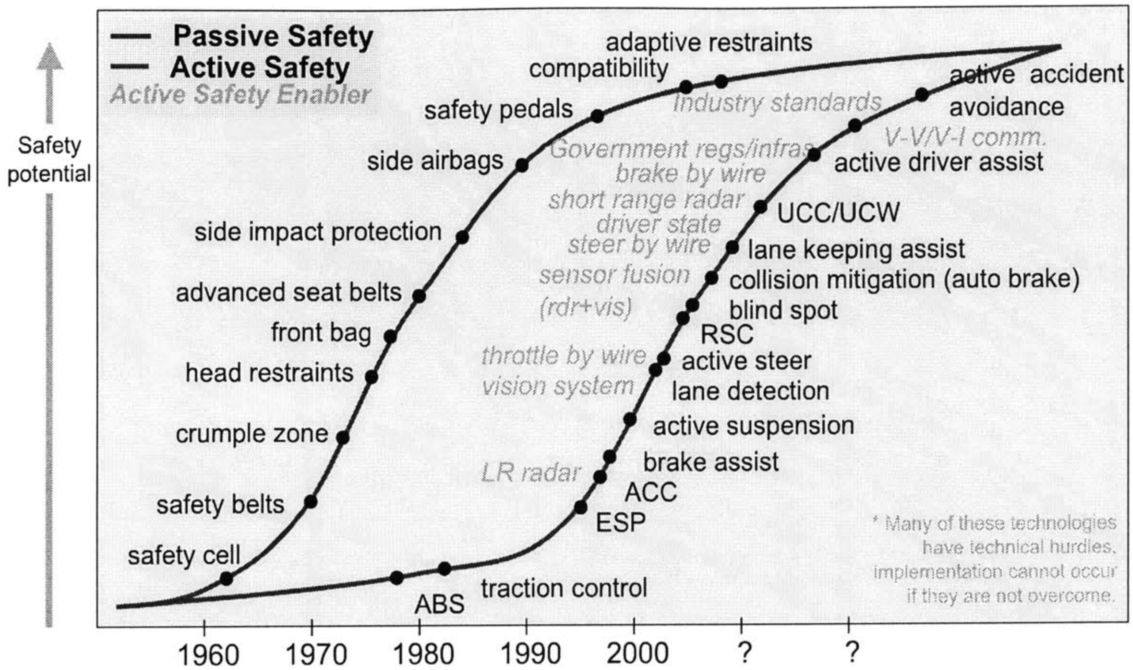

Figure 1-1: Development profile: Active and Passive Safety systems [39]

accidents have already happened.

On the other hand, *Active Safety* systems are generally defined within global automotive industries as systems which contribute to the *active avoidance* of road accidents, as opposed to Passive Safety features [39]. They aim to predict whether there is going to be an accident or a near crash situation. They monitor drivers to determine whether they are vigilant enough to drive safely and to cope with emergencies. ABS (Anti-lock brake systems), RSC (Roll Stability Control Systems) and LDW (Lane Departure Warning Systems) are some examples of Active Safety systems.

A myriad of Active Safety systems have received attention from major automobile companies, and are being developed. The chronological development profile of both Passive and Active safety features is shown in Fig. 1-1 [39], which clearly shows a distinction between both features. Whereas the development of Passive Safety systems is nearly saturated, the development of Active Safety systems is accelerating. The Active Safety Enablers shown in Fig. 1-1 describe technologies essential for Active Safety systems. Many Active Safety systems require advanced sensor systems for implementation.

As shown in Fig. 1-1, a majority of Active Safety systems aim at assisting drivers; they help drivers to keep lane positions, to brake, to steer, and to monitor blind spots. There is a growing consensus that human errors of attention and vigilance are among the most common causes of transportation accidents [30, 31, 64, 129]. We often blame vehicles for any malfunctions, but a majority of transportation accidents originate from humans; drivers, passengers, or pedestrians. Statistics from the U.S.A. and Europe show that among the diverse causes of transportation accidents, approximately 10 to 30 percent of accidents involves sleep and fatigue [113]. Furthermore, their involvement in fatal accidents is especially high [122]. During the period of 2000-2005, the percentage of fatal accidents attributable to sleepiness and inattention varied from 19.6% to 25.1% [41].

Sleep and fatigue involvement in transportation accidents is undoubtedly global. For example, a pile-up crash occurred on January 13, 2007 on Northbound Kyungbu-Highway in South Korea. This crash killed 9 people, injured 23, and crushed all five vehicles involved. Fig. 1-2 [68] shows damaged vehicles from the accident. This tragic accident has turned out to be initiated by a drowsy driver.

This is just one episode showing that the consequences of drowsy driving could be severe, yet drowsy driving is unregulated. Although the danger of drowsy driving has been recognized, no efficient methods for regulating or managing fatigue-related transportation accidents have been enacted yet, as there have been for DUI (Driving Under the Influence). This thesis focuses on addressing the following questions:

- Can we detect drowsiness of drivers before an accident happens?
- What kind of technology is reliable and efficient in detecting drowsy driving?
- How dangerous is drowsy driving compared to other impaired driving such as DUI?
- What kind of countermeasures for drowsy driving are effective?

In the U.S.A., there are many ongoing efforts at Federal, industrial, and in non-govermental organizations toward technological development for monitoring drivers' behavior in order to manage performance-impairment caused by fatigue [47]. We

Figure 1-2: Drowsy driving often leads to severe consequences. [68]

believe that research on drowsy driving is a key to manage fatigue problems in transportation.

1.2 Problem Statement

In this section we define the problems and issues that we will address throughout the thesis. As a way to identify the problems within the context of transportation accident management, we introduce the Haddon Matrix, which is the most commonly used paradigm in the field of injury prevention.

The Haddon matrix [46] is a matrix of categories. It enables us to systematically analyze transportation accidents by considering causal factors and contributing factors. Active and Passive Safety systems can be also mapped into the Haddon matrix. A Haddon matrix categorizing automobile collisions is shown in Table 1.1. The causal factors, shown in each row of the matrix, categorize problems into three different time frames: before the accident, during the accident, and after the accident. The contributing factors, shown in each column, divide the problems into three attributes: human, vehicle, and environment. Thus, the Haddon matrix has a total of 9 categories of intervention to prevent transportation accidents.

Table 1.1: Haddon Matrix for automobile collision [39, 46]

<table>
<tr><th></th><th>Human</th><th>Vehicle</th><th>Environment</th></tr>
<tr><td rowspan="2">Pre-event
(Accident Avoidance)</td><td>Motor skills, Cognitive function</td><td>Active Safety (Ex: ABS, LDW, CAS, RSC)</td><td rowspan="2">A nation wide roadway based communications, Weather cond.</td></tr>
<tr><td colspan="2">Detection of Human Drowsiness</td></tr>
<tr><td>Event
(Occupant Protection)</td><td>Technology and proper use</td><td>Passive Safety (Ex: Air bags, Seat belt)</td><td>Road design for injury mitigation</td></tr>
<tr><td>Post-event
(Injury mitigation)</td><td>Telematics</td><td>Automatic crash notification</td><td>Emergency medical services</td></tr>
</table>

For example, Active and Passive Safety systems appear in the second column (the vehicle-attribute column), since both features are mainly installed and operated in vehicles. However, they are categorized into two different time frames depending on their purpose, as described in Section 1.1. Thus, Active Safety systems reside in the first row (pre-event), whereas Passive Safety systems belong to the second row (during the event). Environmental attributes, shown in the third column, are examples of infrastructures that can predict, prevent or mitigate transportation accidents: a nation-wide roadway-based communication system, smarter and safer roadway design, better emergency medical services, etc. Environment (Road) and Vehicles have recently received considerable attention [114], such as ITS (Intelligent Transportation Systems). However, drivers behind the wheel are considered to be the most important factor in analyzing automobile collisions [114].

Among a variety of Active Safety systems, our interest centers on *detection of drowsy driving.* Detection of human drowsiness resides in both the Human & Pre-event and Vehicle & Pre-event categories, i.e. the first and second columns of the first row. This implies that our research is twofold; we need to understand the characteristics of drowsy drivers (the human attribute) and at the same time find out how to design a system to detect human drowsiness (the vehicle attribute).

The first problem encompasses the characteristics of drowsy driving. People are aware of the danger of drowsy driving, but only peripherally. How dangerous is drowsy driving compared to normal driving or other impaired driving? Many people guess that drowsy drivers may have bad lane tracking performance compared to normal drivers. Can this belief be verified by experiments or field tests?

Many experiments [16, 32, 33, 34, 69, 80, 127] have shown that response time deteriorates significantly as drivers are sleep-deprived. An experiment investigated subjects' ability to memorize nonsense syllables (attentiveness), to find a correct number from a set of seven digit numbers (rapidity), and to erase as many alphabet letter A's as possible in a certain amount of time (accuracy). It has been found out that attentiveness and rapidity suffer more than accuracy [138] when people are sleep-deprived. However, few of these studies have been performed for sleep-deprived *drivers*. We are interested in seeing if sleep-deprived drivers show different characteristics for various driving tasks and secondary tasks. When we get drowsy, which part of our driving abilities is affected first or most significantly?

Recently, studies [20, 58, 132, 145] have tried to find a mapping between driving tasks and areas of brain activities by using imaging techniques such as fMRI (Functional Magnetic Resonance Imaging). It shows the activated brain areas of subjects under a variety of simulated driving circumstances. It is beyond the scope of this study to find the exact mapping between brain areas and driving tasks for various sleep levels. We study several driving tasks and secondary tasks that have different characteristics, while trying to determine whether there exist any tasks during which driver performance is more vulnerable to drowsiness than others. We shows how *task types* and *sleep-deprivation levels* affect driving performance and provides design strategies for building drowsiness-detection devices.

Our study does not employ physiological signals such as EEG (Electrocephalography), but deals with driver-vehicle data including driver reaction and vehicle states. Considering that sleep and wakefulness are often defined by EEG signals, we can view

Figure 1-3: Can we detect drowsy drivers? (Photo from [137])

our methodology as an indirect way of analyzing and/or detecting drowsy driving. This approach is cost-effective because we do not need any complicated sensor systems or peripherals, and the result can be more practical and directly related to driving. To tackle the problem of identifying the characteristics of drowsy driving, human-in-the-loop experiments are designed and performed. Results from this stage are essential for the second problem: detection of drowsy driving based on driver-vehicle data.

The second problem focuses on devising a systematic method to detect drowsy driving, which can be considered dual to the first problem. We first desire to differentiate between drowsy and normal drivers, and then to infer driver states only based on their performance or vehicle states, i.e., driver-vehicle data.

A variety of methods for the detection of drowsiness have been developed by many research groups. They can be classified in terms of detection techniques, which are described in Chapter 2. We do not aim to develop another detection technique, but to present a universal and systematic methodology for inferring the state of drivers based on driver-vehicle data.

In case of DUI, BAC (Blood Alcohol Content or Blood Alcohol Concentration) is usually estimated from breath alcohol concentration. Tolerance to alcohol varies from person to person depending on weight, gender, body fat percentage, etc. However, in many countries, the estimated BAC is generally utilized to detect drunken drivers. If we can establish such a standard for drowsy driving that can be universally accepted, it will contribute to transportation safety. Furthermore, by actively predicting the state of drivers rather than detecting drowsiness after it has occurred, we can manage fatigue in transportation more effectively.

We aim to establish a systematic methodology for detecting drowsy drivers utilizing the Bayesian Network paradigm and to quantify the associated results using driver-vehicle data obtained from the simulator-based human-in-the-loop experiment. Time-varying characteristics of drowsiness are also considered. We do not include any physiological signals or physical changes of drivers such as eye closure rate. (Details of physiological signals and physical changes of drivers are elaborated in Chapter 2.)

Countermeasures for drowsy driving, i.e. how and what we do with the detection method, are interesting topics, but are a completely separate problem from detection. They are beyond the scope of this study, but further research is necessary for proper installation of drowsy driver detection systems.

1.3 Contributions

In terms of the problems discussed in the previous section, this thesis yields practical outcomes for managing drowsy driving. The contributions can be stated as follows:

- Drowsy driving characteristics are comprehensively analyzed through a simulator-based human-in-the-loop experiment. Subjects who have different sleep-deprivation levels are asked to perform common driving tasks and various secondary tasks in the simulator. The experimental data shows that performance in various driving tasks is not affected uniformly by sleep-deprivation; under sleep-deprivation, the rule-based tasks, such as Psychomotor Vigilance Tasks, deteriorate to a greater extent than the skill-based tasks, such as Straight Lane Tracking Tasks with no disturbances. This result demonstrates a latent risk of sleep-deprived drivers, and points to a possible design of drowsy driver detection systems based on driver-vehicle data.

- Inspired by brain functions related to the human motor control system and the sleep-wake cycle regulators, we introduce an experimental hypothesis that drowsiness affects various driving tasks *non-uniformly*. This approach allows us to understand drivers' performance more profoundly than simple comparison of superficial phenomena. Although it is beyond our scope to prove interactions between the motor systems and the sleep-wake cycle regulators, this idea opens a new engineering-oriented interdisciplinary research field combining human factors and neurosciences.

- We lay the foundation for the systematic management of drowsy driving. In-depth knowledge of the sleep-wake cycle mechanism and of the driver-vehicle system enables us to rigorously define drowsy driving, which is supposedly known from a common sense standpoint. This foundation helps us to organize overall research on drowsy driving. We examine the management of drowsy driving detection from such standpoints as law enforcement and policies, as well as detection techniques.

- We devise a systematic way to infer the state of driver alertness. A basic framework is adopted from the Bayesian Network (BN) paradigm. Two major causes of sleep, sleep-debt and circadian rhythm, are modeled in the framework with various driver-vehicle parameters. We examine both static and dynamic BN structures. Time varying characteristics of drowsy driving are captured in the dynamic BN structure.

- We employ experimental results (driver-vehicle data) for a structural development, which in turn provides us with quantitative outcomes. Performance in varied driving tasks and secondary tasks are utilized to estimate the state of driver alertness. The comprehensive inference probability based on driver-vehicle data presents guidelines for designing a drowsy driver detection system. The result suggests that individual human differences should be considered in the design of such a system, although we are able to observe global trends. This framework can be easily extended if we have more information on driver-vehicle systems such as physiological signals.

- We propose a new probabilistic measure that enables us to provide a low-cost drowsy driver detection system. Once characteristics of other driving impairments (such as DUI) characteristics are collected, estimates based on driver-vehicle data are applicable to a general driver-state monitoring as well as to drowsy driving.

1.4 Overview of Thesis

This thesis focuses on the interaction issues of drowsy driver detection by driver-vehicle data, and provides a systematic methodology to infer the state of drivers based on driver-vehicle data. The whole contents are structured as follows.

Chapter 2 reviews previous research on fatigue management in transportation. We summarize existing measures including transportation policies and detection techniques mainly developed in the U.S.A. and Europe, and discuss statistics on drowsy driving as well.

Specification of drowsy driving requires us to understand the sleep-wake mechanism, which in turn enables us to clarify the concept of drowsiness. Chapter 3 presents the mechanism of the human sleep-wake cycle along with causes of sleep, and the physiology of the sleep-wake regulation. Definitions of related terminologies including drowsiness, fatigue, and boredom are given as well.

Chapter 4 illustrates general driver-vehicle systems to help understand driving in general. Structures of driver-vehicle system, various types of input to the driver-vehicle system including visual and vestibular inputs, control interface between a driver and a vehicle, and simplified vehicle dynamics are described.

Chapter 5 covers human-in-the-loop experiments using a fixed-based driving simulator, which aims to find out the characteristics of drowsy driving. Experimental objectives, hypothesis, design of experiment, independent and dependent variables, hardware and software set-up, contents of driving scenarios, experiment procedures and subject summary data are included.

Chapter 6 mainly deals with extensive driver-vehicle data analysis to reveal the characteristics of drowsy driving. We analyze performance differences between two different sleep-deprivation groups for various driving tasks, which is followed by order effects and power analysis.

In Chapter 7, we devise a systematic way to detect human drowsiness. Bayesian Network paradigm is introduced, and its framework is built. Using experimental data obtained from Chapter 5, we set up a quantitative guideline. Both static and dynamic Bayesian Networks are applied.

Finally, Chapter 8 provides a summary and future research plans.

Chapter 2

Fatigue Problems in Automobile Operations

Fatigue is one of the primary causes of accidents in transportation, and thus it has naturally attracted wide interest in its research. This chapter summarizes the vast literature on drowsy driving. We first review the history of fatigue problems in transportation. Then, dealing with several causes of fatigue, e.g., long working hours, sleep deprivation, specific time-of-day, etc., we discuss fatigue management through drowsy driver detection and existing countermeasures for drowsy driving from both policy and technical standpoints. Finally, we summarize some critical facts on drowsy driving, including statistics, crash characteristics, and high-risk population groups.

2.1 Historical Perspectives

In 1938, the Interstate Commerce Commission requested that the U.S. Public Health Service should conduct an investigation into CMV (commercial motor vehicles) HOS (hours-of-service) in interstate commerce. This was the first scientific study to address driver fatigue related to HOS. The Public Health Service study bolstered the need for regulatory limitation on HOS to help ensure highway safety [38]. HOS regulations specify the length of on-duty and off-duty time for operators in commercial transportation. The motor carrier HOS regulations were developed in 1937, and have

Table 2.1: Motor carrier hours-of-service regulations [95]

Motor Carrier (49 CFR Part 395)
Drivers may drive for 10 hours or be on duty for 15 hours.
Drivers must have 8 consecutive hours off following a 10/15 hour on-duty period.
If drivers use a sleeper berth, they may split the 8-hour period into two periods as long as neither period is less than 2hours.
Drivers may not exceed 70 hours in 8 days if the carrier operates 7 days a week.
Drivers may not exceed 60 hours in 7 days if the carrier does not operate every day of the week.

remained essentially unchanged [95]. Table 2.1 shows the current hours-of-service regulations for motor carriers [95].

The DOT (U.S. Department of Transportation) has conducted three studies on CMV driver fatigue since the 1970s, none of which has led to changes in the Federal HOS regulations. In 1988, the Congress directed the DOT to conduct research on how HOS regulations, driver fatigue, and the frequency of serious CMV accidents were related to one another. In the same year, the FHWA (Federal Highway Administration) hosted a Symposium on Truck and Bus Driver Fatigue, which brought together experts from motor carrier industries, scientific and medical communities, law enforcement, and public policy.

In the 1990s, driver fatigue has continually grown to be a major concern in industry and public safety. The 1995 FHWA-sponsored Truck and Bus Safety Summit, collecting over 200 national leaders in CMV and highway safety and including a large contingent of drivers, identified driver fatigue as the top priority of CMV safety. Accordingly, the fatigue issue dominates current human factors research on CMV driving safety sponsored by FHWA [38].

The history of drowsy-driver research dates back to the 1950's, beginning with the studies on aircraft pilots [82]. In 1995, the NTSB (National Transportation Safety Board) and NASA (National Aeronautics and Space Administration) cosponsored a symposium to discuss fatigue countermeasures and to demonstrate how they can be applied to prevent accidents in all modes of transportation [95]. Development of the Fatigue Resource Directory is one of the key products in the symposium [126].

A 100-Car Naturalistic Study conducted by NHTSA and Virginia Tech Transportation Institute aims to provide pre-crash data necessary for understanding cause of crashes, to support the development and refinement of crash avoidance countermeasures, and to estimate the potential utility of these countermeasures to reduce crashes and their consequences [96].

Europe also has several large-scale programs in progress under the direction of RTI (Road Transportation Informatics), which is the equivalent to the ITS (Intelligent Transportation Systems) in the U.S.A. Their main programs are DRIVE (Dedicated Road Infrastructure for Vehicle safety in Europe) and PROMETHEUS (Program for European Traffic with Highest Efficiency and Unprecedented Safety) beginning in the late 1980s [18, 35]. In January 2002, the European Commission initiated a three-year project IMMORTAL (Impaired Motorists, Methods of Roadside Testing and Assessment for Licensing), which provided a firm scientific base for the associated legislation [21]. AWAKE (Assessment of driver vigilance and Warning According to traffic risK Estimation) is a European project, targeting to promote road safety and to reduce road accidents due to driver hypo-vigilance [81].

2.1.1 Facts and Statistics on Drowsy Driving

Although estimation and detection methods on drowsy driving vary widely, few dispute that the problem of drowsy driving is inadequately addressed. Fatigue has been estimated to be involved in 2% to 23% of all crashes [37, 33, 115].

The National Highway Traffic Safety Administration conservatively estimates that 100,000 police-reported crashes are caused by drowsy drivers each year. (That is about 1.5% of all crashes.) These crashes result in more than 1,500 fatalities, 71,000 injuries, and an estimated $12.5 billion in diminished productivity and property loss [67].

In 1998, FHWA (Federal Highway Administration) estimated the percentage of large truck crashes involve fatigue as follows: all police-reported crashes (0.53% to 1.3%); all fatal crashes (2.8% to 6.5%); crashes fatal to the truck occupant only (12% to 29%); and crashes fatal to non-truck occupants (1.2% to 2.8%). The FHWA also concluded that more in-depth investigations would yield higher percentages of fatigue-related crashes than those indicated in comparable samples of police accident reports. The 1990 NTSB study of 182 heavy truck accidents that were fatal to drivers showed that 31 percent of the accidents in this sample involved fatigue. The NTSB numbers regarding fatigue-involved accidents are more revealing, as the NTSB's in-depth investigations included such surrogate measures as a 72-hour history of rest and duty times, the amount of sleep in the last 24 hours, and the regularity of the work schedule, etc.

A 1995 study of 107 accidents (62 of which were fatigue-related) examined factors that affected fatigue in heavy truck accidents. [95]. Most accidents occur on highways, and are caused by men (77%) less than 30 years of age (62%). 96% of crashes caused by drowsy drivers involve cars and 3% involve trucks. For truks, however, the expected number of involvements per vehicle life cycle is about four times greater than for cars; this is due to the longer operational lives and higher mileage per year. Truck accidents are more damaging [63].

2.2 Existing Measures

We have shown that research on fatigue problems has a long history with a myriad of topics. This section summarizes fatigue management and its existing countermeasures mainly focusing on drowsy driving detection. We study the existing countermeasures from both policy and technical standpoints.

2.2.1 Transportation Policies

Since 1989, the NTSB has issued more than 70 fatigue-related safety recommendations, mostly as a result of accident investigations, special investigations, or safety studies that identified operator fatigue as a key factor of accidents [95]. In 2004, the NSF (National Sleep Foundation) also recommended the HOS rules. They suggested that policies on HOS: provide for a minimum of 10 consecutive hours of off-duty per 24 hours; include required driver education on how to obtain good sleep and how to recognize signs of reduced alertness and sleep disorders; require automated, on-board monitoring of driving times, systems which are used effectively in other countries; encourage effective screening of commercial drivers' health for possible sleep disorders, excessive sleepiness, and medications that may cause sleepiness; should not include penalties and should minimize lost work time for drivers with sleep disorders provided they comply with effective treatment; and should apply to bus drivers as well as other commercial drivers.

NCSDR (National Center on Sleep Disorders Research) and NHTSA expert panels on driver fatigue [122] recommend three priorities for an educational campaign: 1) educate young males (ages 16 to 24) about drowsy driving and how to reduce lifestyle-related risk; 2) promote shoulder rumble strips as an effective countermeasure for drowsy driving; in the same context, raise public awareness about drowsy-driving risks and how to reduce them; and 3) educate shift workers about the risks of drowsy-driving and how to reduce them.

Law Enforcement

The first federal bill focusing on drowsy driving was introduced in the House of Representatives in October 2002 by Republican Robert Andrews [94]. The bill, HR 5543, is called *Maggie's Law: National Drowsy Driving Act of 2002*. It was named after Maggie McDonnell, who had been killed by a drowsy driver on July 20, 1997 when her car had been hit head-on by a van that had crossed three traffic lanes. The van driver confessed that he had not slept for 30 hours and also smoked a crack of cocaine before the accident. Since the jury was not allowed to consider driver fatigue as a factor, he was only convicted of careless driving and fined $ 200 [94]. This tragic accident caused Maggie's mother, Carol McDonell, to begin lobbying the New Jersey legislature to enact a law that would punish those who kill or injure others as a result of their voluntary fatigued driving. The New Jersey State Senate passed Maggie's Law and established fatigued driving as recklessness under the vehicular homicide statue on June 23, 2003.

The law narrowly defines *fatigue* as being without sleep for a period in excess of 24 consecutive hours. Under Maggie's Law, anyone causing a fatality after being awake for 24 hours or more can be prosecuted for vehicular homicide. The bill calls for incentives for states and communities to develop traffic safety programs to reduce crashes related to driver fatigue and sleep deprivation. The legislation also calls for training police officers, revising the driver's education curriculum, reporting fatigue-related crashes on police report forms in a standardized way, and promoting countermeasures such as continuous shoulder rumble strips and rest areas [94].

Currently, a number of states are considering similar drowsy driving legislation, including New York, Massachusetts, Tennessee, Oregon, Kentucky, and Illinois. A list of pending bills in state legislatures across the U.S.A. addressing drowsy driving and other sleep-related transportation issues can be found in [94].

2.2.2 Fatigue Detection Techniques

Along with transportation policies, reliable and applicable drowsy driving detection techniques are essential for fatigue management. Many researchers have developed a variety of detection methods for drowsiness, which can be classified in terms of their specific techniques [12, 61, 136, 143].

Detection by Physiological Signals

This method is based on the fact that such physiological signals as pulse rate, EEG (electrocenphalography), ECG/EKG (electrocardiogram), and electrodermal activity show different patterns at different human-vigilance levels.

EEG is a sensitive measure of sleepiness, which uses the fact that changes in theta, alpha, and beta frequencies are associated with brief periods of sleepiness (microsleep) and the onset of sleep [5, 11, 48, 50, 65, 73, 93, 94, 107, 108, 143]. (Definitions of EEG waves such as alpha, beta, theta, and gamma frequencies are given in Chapter 3.) For example, lapses of attention are preceded by an increase in low frequency EEG activity, and are also accompanied by a significant increase in alpha and theta activity [27, 114]. The changes in the EEG, as sleepiness develops, are distinct enough to reliably identify sleepiness although the simultaneous use of the EOG (electrooculogram) is highly recommended [36, 143]. The followings are some examples of detection devices based on physiological measures [143].

The *ABM Drowsiness Monitoring Device (DMD)* records EEG via telemetry to detect drowsiness. The system requires an operator to wear a baseball cap containing disposable electrodes. It gives an auditory alert when EEG-determined drowsiness indicator exceeds a threshold.

The *EEG Based Algorithm to Detect Different Levels of Driver Fatigue* uses delta, theta, and alpha activity of the EEG to detect "early, medium, and late" sleepiness.

The *Engine Driver Vigilance Telemetric Control System 3rd Generation (ED-VTCS)* measures electrodermal activities and reactions. Operators are required to wear watch-type sensors. The system activates an auditory alarm when alertness falls below the critical level.

The biggest drawback associated with the EEG as an on-road drowsiness detection device is the difficulty in obtaining recordings under natural driving conditions, which makes it a somewhat unrealistic option for the detection of fatigue [136]. Practical problems associated with using the EEG as a sleepiness detection mechanism, such as the requirement for scalp electrodes, have not been addressed [143].

Detection by Physical Changes of Drivers

Any physical changes related to head position, wrist activity, eye closure rate, blinking behavior, saccadic eye movement patterns, pupil size, eye point of regard, and eyelid movement can be monitored to help detect drowsiness of drivers [8, 9, 12, 23, 33, 42, 43, 67, 77, 143]. A majority of drowsy driver detection systems are based on indices of eye activity, as are summarized in Table 2.3 [143]. Fig. 2-1 shows a display of FaceLAB, one of such systems.

Some examples of detection devices based on wrist activity or head movement are Actiwatch-alert (measures wrist inactivity associated with sleep), Doze Alert (measures head-tilt as sleep occurs), Driver Alert Warning Device (measures head-tilt via pressure device on neck), EPAM (Measures wrist inactivity associated with sleep), MicroNodDetection System (monitors head movements, learns typical patterns of

Figure 2-1: FaceLAB's video display window gives a constant view of a subject's face and tracking features [116]

movement, and detects those associated with drowsiness), and StayAlert (detects head droop by detecting chin contact with device worn around neck) [143].

The sensors or devices for detecting physical changes usually do not interfere with drivers directly, although some movement restriction may exist. However, while blinks are clearly sensitive to sleepiness, there is a complex relationship between blinking activity, visual information processing (which usually suppresses blinks) and sleepiness [143]. On the other hand, in such situations as micro-sleeps, this method cannot detect drowsiness, and the false alarm rate is not yet acceptable for assessing driver drowsiness.

Detection by Driver-Vehicle Data

Driver-vehicle data including steering angle, throttle/brake input, and speed can be chosen to help detect drowsiness of drivers [24, 49, 89, 99, 100, 114, 123, 130, 142]. Some secondary tasks which periodically request responses from drivers can also be employed [33, 69, 135].

The most frequently measured parameter is the frequency of steering wheel movements, which decreases as the driving period grows. Conversely, when a subject is distracted by a rich environment, steering wheel movements are often frequent. SWRR (Steering Wheel Reversal Rate) can be obtained by counting on oscillation numbers of the steering wheel when the amplitude is lower or equal to a certain maximum value varying from .5 to 10 degrees. On high vigilance periods small amplitudes of steering wheel movements are frequent, whereas great corrections predominate during low vigilance states [114]. The underlying presumption is that an alert driver makes a comparatively large number of fine-steering adjustments to cope with the driving task and makes a relatively few number of large-steering ones, except when deliberately changing lanes to pass other vehicles [79].

SDLP (standard deviation of lateral position) or standard deviation of steering wheel movements increases rapidly after the first 30 minutes of driving. Standard deviation of the steering wheel is more affected by road curvature [63]. Lane tracking variability is increased in prolonged wakefulness [7]. Drivers who lose alertness will, because of lapses in information processing, cause their vehicle to wander somewhat within the traffic lane, possibly to leave the lane, or to go off onto the road shoulder [79].

A fatigued driver permits himself more frequently to face situations requiring abrupt changes in speed. His/her ability to maintain a steady cruising is impaired, which results in increased variations on his/her intended speed [79]. Off-road incidents also increase with prolonged wakefulness [7]. Standard deviation of vehicle speed increases after 3 hours of driving [7, 114]. However, no significant velocity variation is found between 2 and 11 hours of driving [12]. The drivers suffering from loss of alertness are more prone to follow a vehicle ahead in a risky short distance and in high closure rates [79], although some drivers affected by fatigue may attempt to reduce their overall velocity [12].

A task focusing on measuring operator's reaction time called Psychomotor Vigilance Task (PVT) shows noticeable differences between alert and drowsy drivers [32, 33, 34, 69, 80, 133]. Increased reaction time by presumably fatigued drivers in response to some injected signal can be displayed either visually or aurally [79].

Table 2.2 shows some sleep detection devices based on driver-vehicle performances. Detailed descriptions for each system and contact informations can be found in [143].

This method characterizes the vigilance states of drivers by comparing the reactions of the driver-vehicle system with a pre-determined threshold. However, this threshold

Table 2.2: Sleep detection devices based on driver-vehicle performances [143]

Name of device	Description
APRB/ACARP Device for Monitoring Haul Truck Operator Alertness	Uses secondary tasks to estimate alertness via an auditory and visual reaction time task (tailored to individuals). Used in mining industry trucks.
DAS 2000 Road Alert System	Measures drivers' acceleration, braking, gear-changing, lane deviation and distances between vehicles
FMD-Fatigue Monitoring Device	Auditory and visual reaction time test. Response pads on steering wheel. Used in mining trucks.
Roadguard	Is a secondary task comprising a reaction task. Only operates when vehicle is in top-gear
Safety Driver Advisor	Learns normal driver steering movements and detects deviations from normal. Comprise a driving time measure, a dashboard display of recommended rest-break times and a monitor of erratic steering behaviour. Recommended driving time is 2h for day, 1h for night
SAMG-3Steer	Monitors normal corrective movements of steering wheel
Stay-A-Wake	Monitors speed and steering behaviour.
SAFETRAC	Uses measurement of lane deviation and steering movements

is difficult to define because there exists considerable inconsistency in the reactions of driver-vehicle systems in the beginning stage of drowsiness. Another limiting factor on performance-based measures is decline in performance capacity may occur prior to changes in driver performance [12, 30]. This phenomenon can be attributed to drivers' skills and the ability of more experienced drivers to compensate during a relatively routine driving task, despite their diminished capacity [12].

In fact, it is not sufficient to use one single parameter to detect driver drowsiness [16]. Renner and Mehring [63, 106] conclude that "With ongoing research it became evident that lane departure warning and lane position parameters reflect only one facet of the performance decrements within fatigued drivers. A fatigued driver can actually keep his vehicle perfectly in the lane, provided the vehicle heading is co-incidentally appropriate for the road curvature ahead. In our studies we found an evidence for intentional short naps on straight road sections, on which the vehicle path was perfect, but the driver was incapable of reacting upon any unexpected event (e.g. front end collision). In order to prevent these dangerous situations of good lateral control without reaction readiness, more complex drowsiness detection techniques had to be developed." Drowsiness detection devices rely on a wide range of different parameters, as there is no single commonly accepted metric to detect driver fatigue in an operational context [143].

2.3 Drowsiness and Driving

Sleepiness and driving form an incompatible and dangerous combination. However, countless people are driving fatigued or drowsy. Most people are aware of the danger of drunken driving, but do not realize that drowsy driving can be as much or more fatal. Like alcohol, sleepiness slows reaction time, decreases awareness, impairs judgment and increases a risk of crashing [94, 122].

2.3.1 Driving During Onset of Sleep

Definitions of drowsy driving or driver fatigue rely on how the concept of *fatigue* is defined. Fatigue is a general term commonly used to describe the experience of being sleepy, tired, drowsy, or exhausted. While all of these terms have different meanings in research and clinical settings, they tend to be used interchangeably in the traffic safety and transportation fields [36]. In Chapter 3 we define terminologies related to drowsy driving after reviewing the mechanism of the sleep-wake cycle.

There are many underlying causes of sleepiness, fatigue and drowsy driving, for example, sleep loss from restriction or too little sleep, interruption or fragmented sleep, chronic sleep debt, circadian factors associated with driving patterns or work schedules, undiagnosed or untreated sleep disorders, time spent on a task, use of sedating medications, and consumption of alcohol when already tired. These factors have cumulative effects, and a combination of any of these can greatly increase the risk of fatigue-related crashes. In this thesis, we mainly focus on drowsy driving caused by sleep restrictions.

Although explicit sleep-onset episodes often cause the most serious performance failures, some performance effects resulting from sleepiness can occur without microsleeps [30, 32]. This implies that the popular belief that falling asleep is the only cause of fatigue-related accidents is inaccurate. There are moments a driver still looks awake (eyes wide open) but does not process any information. These *looking without seeing* moments are dangerous and need to be captured by an effective system [106]. Objective measures on both chronic and situational (acute) sleepiness are required [122].

2.3.2 Challenges in Driver State Estimation

The difficulty in determining the incident of fatigue-related accidents is due, at least in part, to the difficulty in identifying fatigue as a causal or contributing factor in accidents [95]. Unlike alcohol-related crashes, no blood, breath, or other objective test for sleepiness behind the wheel currently exists, which investigators could give to a driver at a crash scene. This makes police training in identifying drowsiness as a crash factor very difficult [94].

It would be certainly useful to develop on-line drowsy driver detection systems, and a variety of approaches are explained in detail in Section 2.2.2. In this Section, we have studied advantages and disadvantages of each method. It suggests that in the near future some technologies should be deployed to prevent or at least limit certain catastrophic outcomes due to drowsy driving [47], although much validation remains to achieve this goal. *The ultimate challenge lies in the human* [47], mainly in inter-individual differences in responses to sleep loss or drowsiness. We address this issue in Chapter 7 in the framework developed for drowsy driver detection based on driver-vehicle data.

2.3.3 Crash Characteristics and High-Risk Population Groups in Drowsy Driving

Crash characteristics

At present, it is nearly impossible to determine with certainty the cause of a fatal crash where drowsy driving is suspected. However, there are a number of clues that tell investigators that a driver falls asleep at a crash scene. For example, drowsy driving accidents usually involve only one vehicle with a driver alone, and the injuries tend to be serious or fatal. Also, skid marks or evidence of other evasive maneuvers are usually absent from the drowsy driving crash scene [94].

A typical crash related to sleepiness has the following characteristics [111, 122]:

- Accidents occur during late night, early morning, or midafternoon; Drowsy-driving crashes occur predominantly after midnight, with a smaller secondary peak in the midafternoon. Studies on commercial drivers show a similar pattern. Nighttime and midafternoon peaks are consistent with human circadian sleepiness patterns.

- The crash is likely to be serious; The morbidity and mortality associated with drowsy driving crashes are high, presumably due to higher speeds and delayed reaction time. In North Carolina, these crashes resulted in more injury than other nonalcohol-related crashes. Fatalities occurred in 1.4% and 0.5%, respectively.

- A single vehicle leaves the roadway; According to the survey on New York State drivers about their lifetime experience with drowsy driving, almost one-half of those who had experienced a fall-asleep or drowsy-driving crash reported a single-vehicle roadway departure; about one-fourth of those who had fallen alseep without crash also reported going off the road.

- The crash occurs on a high-speed road. Most fatigue-related crashes tend to occur on higher speed roads in non-urban areas on account of more long-distance nighttime driving on highways.

- The driver does not attempt to avoid a crash; Drowsy drivers are less likely than alert drivers to take corrective actions before a crash. Anecdotal reports also claim that evidence of a corrective maneuver, such as skid marks or brake lights, is usually absent in fall-asleep crashes.

- The driver is alone in the vehicle; 82% of drowsy-driving crashes occured in a single occupancy vehicle according to in the New Yor State survey of lifetime incidents.

High-Risk Population Groups in Drowsy Driving

Although no drivers are immune from the risk of drowsiness, the following three population groups are at higher risk against drowsy driving [110, 122]:

- Young people, especially young men: The definition of *young* falls between the ages of 16 to 29 year-old. Virtually all studies that analyzed data by gender and age group found that young people, males in particular, are most frequently involved in fall-asleep crashes. The discrepancy between genders is not clearly understood, as both young men and women are likely to be chronically sleep-deprived.

- Shift workers; Circadian phase disruptions caused by rotating shift work are associated with lapses of attention, increased reaction time, and performance deterioration. Most shift workers have occasional sleep disturbances, and approximately one-third of them complain of fatigue.

- People with untreated sleep apnea syndrome (SAS) and narcolepsy; Although the absolute number of crashes is low, the incidence of risk grows among people with untreated SAS and narcolepsy.

Because of commercial motor vehicle drivers' far greater mileage exposure and other factors, the risk of commercial drivers against a fatigue-related crash is far greater than that of non-commercial drivers. Other competing crash factors such as alcohol and speeding are less common among commercial drivers, and thus less critical than fatigue [47].

Although we have analyzed high risk population groups, most drivers are exposed to drowsy driving. 51% of Americans reported that they drove while feeling drowsy in the past year; 17% said they actually dozed off behind the wheel [94].

Before Thomas Edison's invention of the light bulb, people slept for an average of 10 hours a night; today American average sleep hours per night are 6.9 hours on weeknights and 7.5 hours on weekends [94]. A survey from [36] estimates 6.8 hours, whose distribution is shown in Fig. 2-2. Considering that sleep deprivation

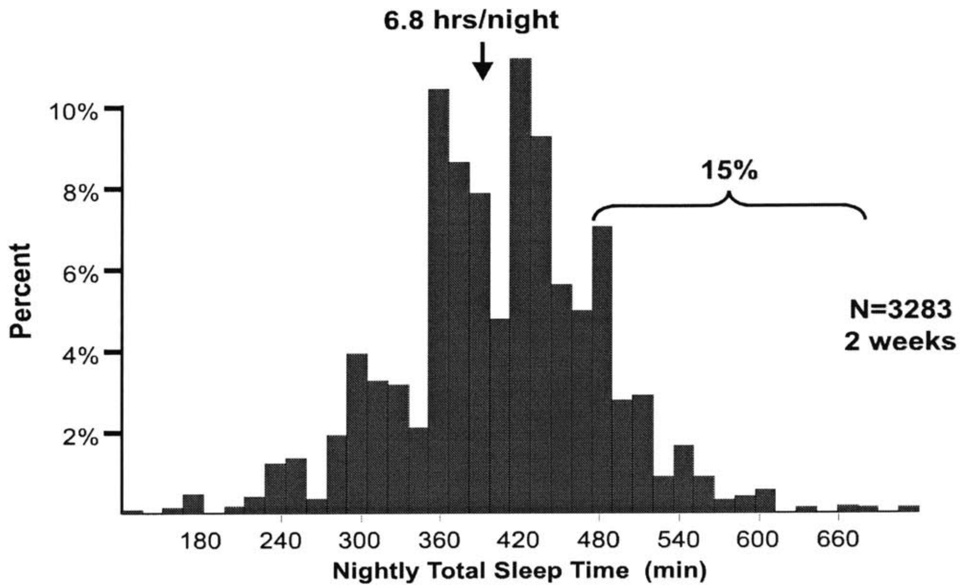

Figure 2-2: Reported mean total nightly sleep time [36]

accumulates with time [135], we see that most populations are under the risk of drowsy driving.

Table 2.3: Sleep detection devices based on eye activity [143]

Name of device	Description
Alert driver	Monitors eye droop, pupil occlusion and eye closure via a camera. Uses image neural nets, fuzzy logic to locate subject's eyes. Is also model-based
CoPilot	Detects percentage of time eyes are closed over a specified time interval (PERCLOS systems) via infrared camera system
DaimlerChrysler EyeGaze Detection System	Measures eye gaze via dashboard camera
Expresseye	Measures fixation, gaze control, and saccadic eye movement to a target. Uses infrared light corneal reflection technique
EyeHead	Measures eye position, head position, and eye to point of fixation distance. Uses a magnetic head tracker
Eye-Gaze System	Measures gaze-direction via corneal reflection technique. Also measures pupil diameter, blinking, and eye fixation
Eyeputer	Records eye movements via corneal reflection technique
ETS-PC Eye Tracking System	Detects eye closure via a camera
FaceLAB 2.0	Measures eye-gaze and eye closure. Uses PERCLOS fatigue assessment scale
IM-Blinkometer	Detects blinks using a piezoelectric adhesive disk attached to canthus of the eye
MTI AM eye	Detects eye blinks. Measures ratio of closed to open eyes to detect sleepiness. Uses infrared reflectance
Nissan Drowsy/Inattentive Driver Warning	Uses image processing to monitor eyelid movements
Onguard	Measures eye closure, activates an alarm after 0.5s closure period. Uses infrared reflectance
OptalertTM	Uses infrared oculography to detect eyelid movements during blinking and eye closure. The system is being further developed to measure intersaccade interval
PERCLOS	Detects eye closure using infrared, retinal-reflectance device. Measures duration of blinks and eye closures, and proportion of time eyes closed over a specified timer interval
Photo Driven Alert System	Worn on ear and measures blink rate
SafetyScopeTM	Ocular system in quantifying sleepiness
SmartEye	Detects head position and point of gaze via image processing
Toyota Driver Drowsiness Detection and Warning System	Detects eyelid movement using camera mounted on rear-view mirror
Vehicle Drivers Anti-Dozing Aid (VDAD)	Measures eye closure and head movement via infrared reflectance. Developed by US military

Chapter 3

Sleep-Wake Cycle and Drowsiness

We have examined general issues of drowsy driving and their existing measures, but we have not defined *drowsy* driving yet. Specification of drowsy driving requires us to understand the sleep-wake mechanism, which in turn enables us to clarify the concept of drowsiness. This chapter briefly reviews the mechanism of the human sleep-wake cycle along with the causes of sleep and the physiology of the sleep-wake regulation. Definitions of related terminologies including drowsiness, fatigue, and boredom are given as well.

3.1 Sleep-Wake Cycle

Human exhibit sleep-wake behaviors. They usually stay awake in the daytime and sleep at night. Until recently, wakefulness has been considered to be good and desirable, on the other hand, sleep to be bad, although unavoidable [65]. The view that sleep is the contrary to wakefulness has been popular and traditional since the days of Aristotle, who declared [65]:

> First, then, this much is clear, that waking and sleep appertain to the same part of the animal, inasmuch as they are opposite, and sleep is evidently a privation of waking. For contraries, in natural as well as in all other matters, are seen always to present themselves in the same subject, and to be affections of the same: examples are health and sickness, beauty and ugliness, strength and weakness, sight and blindness,

Figure 3-1: Various sleep images (pictures collected from [94])

hearing and deafness.

Until the early 20th century, sleep is believed to be a passive state. People believed that they fell a sleep because they closed their eyes and let them lie down; they thought that they could control sleep by reducing external stimuli through manipulating their body.

Much more has been discovered about sleep in the past 80 years than in the preceding many thousand years. Recently researchers have discovered that sleep is, indeed, a dynamic behavior instead of a passive state caused by a decrease in stimulus level to human. Sleep is an active state of the brain and is involuntary. A renowned sleep scientist, Allan Hobson [48], phrases the central role of the brain in sleep (by rephrasing Abraham Lincoln's famous declaration about government): *sleep is of the brain, by the brain, and for the brain.* Hobson says that it is to be emphasized that for sleep to occur a highly developed brain is necessary, not to say that no other part of the body participates in or benefits from sleep.

Sleep is of the brain not just because it is fully developed only in animals having elaborate brains, but because measurable changes in the electrical activity of the brain distinctively define sleep. On the other hand, the behavioral symptoms of sleep - a lying down posture, closed eyes, and lack of responsiveness to stimulus - can be easily faked.

The brain controls itself so as to produce sleep. We can fall asleep and never even recognize how difficult we try to stay awake or to sleep. We may be able to try not to sleep or to sleep long, but it does not belong to our *free-will*, to govern sleep or wakefulness. The brain's own electrical activity changes in response to signals from networks of brain cells. (We will examine the neural systems regulating the sleep-wake cycle in Section 3.1.3.) Finally, the brain is the prime beneficiary of sleep, which leads to its functional improvement [48].

Sleep is known to be vital to human life. Although scientists are still trying to find out *why* people need to sleep, research on animals shows that sleep is necessary for survival [93]. The need for sleep is probably as compelling as or more than other drives such as eating or drinking. Many researchers consent that adequate sleep is essential for health and wellness. Nobody is invulnerable to drowsiness but some people have problems falling into sleep or waking up. The most prevalent sleep disorders include insomnia, sleep apnea, and narcolepsy and they harass daily-based life. Each year, at least 40 million people in the United States suffer from chronic sleep disorders, and another 30 million are troubled by transient or occasional sleep problems [93].

We will focus on sleep causes in the following section, and then briefly review how the brain regulates the sleep-wake cycle, i.e., the mechanism of sleep-wake cycle.

3.1.1 Causes of Sleep

What causes us to sleep or to be awakened? What makes us sleep at night and wake up in the morning *regularly*? Is it because we close our eyes and lay down in bed? Is it because we are bored or provided a quiet environment? It has been believed that the external environmental factors cause sleep or wakefulness. The truth is that we have an embedded sleep-wake cycle regulator controlled by a combination of two internal influences; *circadian pacemaker* and *homeostasis* are two primary neurobiological forces that govern the sleep-wake cycle [5, 29, 30, 36].

Environmental factors such as stress, noise, light, excitement, anger, pain and sleep-fragment are known to affect the sleep-wake cycle as well. However, in contrast to our common belief, they do not *cause* us to sleep, but simply *unmask* any tendency to fall asleep that is present already. As a matter of fact, only a small amount of stimulation is enough to keep us awake if sleep debt, i.e., the cumulative effect of not sleeping enough, is trivial. However, we can easily fall into sleep in a very noisy concert if sleep debt is huge.

It is frequently misunderstood that boredom can cause sleepiness. It may unmask sleep in human who is either originally sleep-deprived or in circadian sleep-peaks, but does *not* cause sleepiness in itself [36]. Masking is a critical concept for understanding sleep in terms of the sleep-wake cycle. It is common that people who have chronic sleep deprivation can mask their level of sleepiness at workplace. However, when they sit still and become unmotivated after work, sleep is unmasked and arises quickly [101, 133].

Kleitman [65] also pointed out that the appearance of the sleepless person seemed quite normal particularly during daytime when he was engaged in some forms of muscular activity. However, the subject had to be supervised very closely, as it rendered him extremely sleepy to sit down even during daytime. But the subject usually remained fully awakened while performing a test that required his active participation.

Let us examine the two neurobiological forces governing the sleep-wake cycle: the homeostasis and the circadian pacemaker.

Homeostasis

The homeostasis is a process by which our body maintains a *steady state* of internal conditions such as blood pressure, body temperature, and acid-base balance [93]. The amount of sleep we have per night is also under homeostatic control [29, 30, 48, 93, 94, 128, 135]. The homeostasis is related to the amount of sleep we have and the time we wake up. The longer the period of wakefulness is, the more sleep propensity builds and the more difficult we resist it. Thus, we consider the homeostasis as a *sleep-dependent* component of the sleep [36].

Although the neurotransmitters of the sleep homeostatic process are not fully understood, there is an evidence to indicate that adenosine may be the sleep-inducing chemical [93]. As long as we keep awake, blood levels of adenosine rise continuously, resulting in a growing need for sleep that becomes more and more difficult to resist. During sleep, on the other hand, levels of adenosine decrease, thereby reducing the need for sleep [93].

Then, how much sleep do we need? Someone says that general adults should have 8.2 hours per 24 hours with very little variability [36]. Other studies showed that healthy adults needed seven to eight hours every night. We call it *basal sleep need*, the amount of sleep our bodies need on a regular basis for optimal performance. Thus, we can assume that human basal sleep need is about 8 hours per 24 hours.

In addition to the basal sleep need, we also need to consider sleep debt to figure out how much sleep we need for each day. Sleep debt is the accumulated lack of sleep resulting from poor sleep habits, sickness, awakenings due to environmental factors or other causes. Even the loss of one hour of sleep time for several days can be accumulated and influence our daily life negatively [36]. Estimating the necessary amount of sleep is complicated when we have unresolved sleep debt [94]. It is known that we need at least 7 consecutive nights of 8-hour full sleep to remove sleep debts accumulated previously [36].

On the other hand, some claims that there is no *magic* number for the amount of sleep we need; they consider that sleep need varies between individuals not only different from age groups [94]. Someone may need to sleep at most 7 hours a night, whereas someone else may clearly need at least nine hours to have a happy, productive life. This suggests that long and short sleepers appear to be born, not made [48].

Circadian Pacemaker

The circadian pacemaker is an internal body clock that completes a cycle approximately every 24 hours, and it refers to the cyclical changes such as fluctuations in

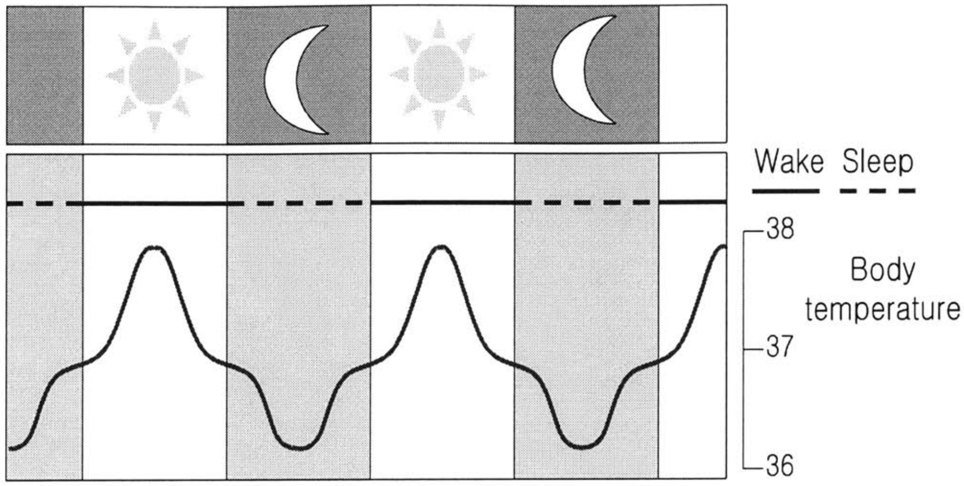

Figure 3-2: A schematic diagram of the circadian rhythm, redrawn from [48]

body temperature, hormone levels, and sleep. The biological clock consists of a group of neurons in the hypothalamus of the brain called suprachiasmatic nucleus (SCN).

The circadian pacemaker is naturally a 25.9 hours cycle which determines when human fall asleep, i.e., when a human subject is isolated from time cues. However, the cycle has become synchronized to 24 hours to correspond with daily activities and the environment surrounding people [48]. In humans, light is the strongest synchronizing agent [93]. Light and darkness are external signals that *set* the biological clock and help determine when we feel necessary to wake up or to go to bed.

The existence of this cycle is thought to be due to: 1) the fluctuation in adrenaline; increase in adrenaline is accompanied by wakefulness and decrease in adrenaline is followed by sleep, and 2) fluctuation in body temperature; body temperature decreases during sleep at night, but it increases as morning approaches. Since body temperature is low during sleep, energy is conserved [5]. Fig. 3-2 shows a schematic rhythm of body temperature and of sleep controlled by the body clock.

Fig. 3-3 shows a conceptual diagram of sleep causes. The homeostasis is a sleep-dependent factor, whereas the circadian rhythm is a sleep-independent. Thus, the homeostasis contributes more and more as days of sleep deprivation increases. However, circadian pacemaker continues its own rhythm regardless of the amount of sleep

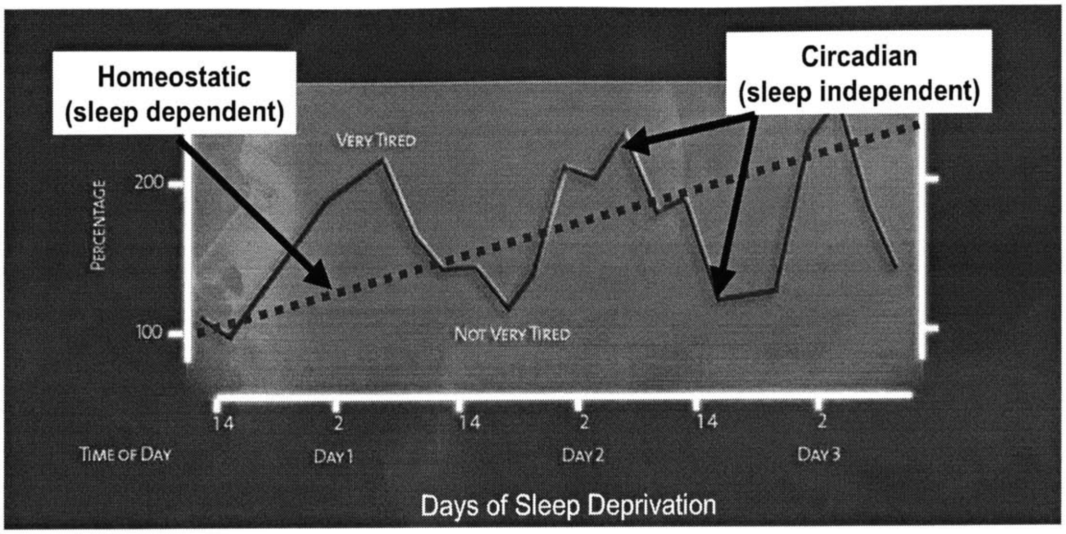

Figure 3-3: Sleep-independent and sleep-dependent factors [36]

deprivation.

The homeostatic factor is known to govern circadian factors to regulate the timing of sleeping and wakefulness; these processes create a predictable pattern of two sleepiness peaks [48, 122]. First sleepiness peak occurs in the middle of night sleep (most commonly at night between 2-4 am) and second sleepiness peak occurs, as we all know by experience, during mid-afternoon, in 12 hours after the first sleepiness peak. This has been referred to as the mid-afternoon, siesta, post-lunch, or post-prandial dip even though it appears to have no relationship to food intake [133].

Researchers developed the sleep-wake cycle model, i.e., the two-process model of sleep-regulation which consists of a homeostatic process and a circadian process. This model has been employed to describe, predict, and understand the sleep-wake regulation in a variety of experimental protocols [2, 3, 134].

3.1.2 EEG of Sleep

Sleep is an active physiological process [48, 93, 65]. While metabolism generally slows down during sleep, all major organs and regulatory systems continue to function. Changes in brain activity are measured by an electroencephalography (EEG).

EEG is a neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp. The resulting traces are known as an

EEG and represent an electrical signal (postsynaptic potentials) from a large number of neurons. Not electric currents, but voltage differences between different parts of the brain are measured [48]. The EEG is capable of detecting changes in electrical activity in the brain on a millisecond-level.

EEG and MEG (magnetoencephalography) have a remarkable merit of high temporal resolution at submillisecond scale, capable of detecting rapid changes of neurophysiologic process. However, these techniques suffer from the ambiguities in defining precise locations of brain activity. On the other hand, fMRI (functional magnetic resonance imaging), using endogenous blood-oxygenation-level-dependent (BOLD) contrast, is another well-established technique for mapping human brain function. In contrast to EEG & MEG, the benefit of fMRI lies in its high spatial resolution; activated brain areas can be localized within millimeter spatial resolution. But the slow response time of the BOLD response limits its capability to characterize how, rather than where, the brain performs its tasks [76].

The amplitude of the EEG signal strongly depends on how *synchronous* the activity of the underlying neurons is. When a group of cells is excited simultaneously, tiny signals sum up to generate one large surface signal. On the other hand, when each cell receives the same amount of excitation spread out in time, the summed signals are meager and irregular. If the synchronous excitation of this group of cells is repeated, the resulting EEG consists of large, rhythmic waves, indicating how synchronous the underlying activity is [11].

EEG signals are categorized by their frequency ranges, and each range is named by Greek letters [11, 48, 50, 94]. *Beta* rhythms are the fastest, greater than 14 Hz, and signal an activated cortex. *Alpha* rhythms are about 8-13 Hz and are associated with quiet, waking states. *Theta* rhythms are 4-7 Hz and occur during some sleep state. *Delta* rhythms are quite slow, less than 4 Hz, often large in amplitude, and are a hallmark of deep sleep [11]. Table 3.1 summarizes these EEG signals.

Sleep can be categorized into distinct states according to the EEG signals [65]. Rapid eye movement(REM) sleep and non-REM (NREM) sleep, which consists of four stages, are two types of sleep [5, 11, 48, 50, 65, 93, 94]. Although the progression of

Table 3.1: Characteristics of EEG signals

EEG signal	Signal frequency	Characteristics
Delta	1-3 Hz	deep sleep
Theta	4-7 Hz	NREM Stage I
Alpha	8-13 Hz	quite, waking states
Beta	> 14 Hz	an activated cortex

EEG waves has been divided into discrete stages, it is actually gradual and continuous [48]. During a normal night, we slide through the stages of NREM, into REM, then back through the NREM stages, repeating the cycle about every 90 minutes. These cycles are examples of *ultradian rhythms*, which have faster period than circadian rhythms [11].

NREM sleep is characterized by a reduction in physiological activity. As it gets deeper, the brain waves as measured by EEG get slower and have greater amplitude, breathing and heart rate slow down, and blood pressure drops [93]. Four stages of NREM sleep is typified as follows [50, 93].

Stage 1 is a time of transition from being awake to falling asleep, which only occupies 5 percent of night. Theta activity, a loss of alpha and often some vertex sharp waves are shown in this stage. (Wakefulness usually show alpha or beta rhythms.)

Around 45 percent of sleep is made up of Stage 2, a period of light sleep during which eye movements stop. This stage contains a mixture of theta activity, sleep spindles, K complexes, which are sudden sharp wave forms, and a few delta waves.

Stage 3 is more of a transition phase from Stage 2 to Stage 4, and constitutes only about 7 percent of sleep in young adult.

When delta activity goes beyond in Stage 3, then the deepest sleep, Stage 4, is reached. It is the most difficult to be awakened during slow wave sleep, i.e., Stage 3 and Stage 4.

REM sleep is an active period of sleep marked by intense brain activity. This stage is also referred to as paradoxical sleep since brain activities during REM are comparable to those during wakefulness. Brain waves are fast and desynchronized, similar to those in the waking state. Most dream occurs in REM sleep [48].

The amount of alpha activity with eyes held either open or closed (to avoid artifacts from blinking) is considered to be related to the level of alertness [133].

3.1.3 Brief Review on Neural Systems Regulating Sleep-Wake Cycle

Drowsiness and sleepiness are manifestations of brain activities. The brain stem contains an extremely complex circuit of interconnecting neurons that provokes arousal when electrically stimulated. This area is called the *reticular formation*. It is a part of the brain stem, and is included in all three components of the brain stem: medulla (in the bottom), pons (in the middle), and midbrain (on the top). Cells from the reticular formation project into the cerebral cortex indirectly, and their excitation of those cells produces arousal or wakefulness [60]. Meanwhile, destruction of the rostal portion of reticular formation produces sleep, which implies that one of its functions is to keep us awake.

The reticular formation is responsible to produce the main neurotransmitters (such as acetylchonline, dopamine, glutamate, asparatate, histamine, serotonin, and norepinephrine) involved in sleep and wakefulness. These neurotransmitters primarily play an excitatory role in the activation and arousal of the corresponding brain areas. Serotonin and norepinephrine are two major neurotransmitters involved in sleep [5]. At the onset of sleep, serotonin is secreted, which increases NREM sleep. Secretion of norepinephrine takes place during REM, and increases REM. Fluctuation between stages of sleep are thought to be due to the secretion of these two neurotransmitters [40]. On the other hand, blood levels of adenosine rise continuously, resulting in a growing need for sleep that becomes more and more difficult to resist. During sleep, on the other hand, levels of adenosine decrease, thereby reducing the need for sleep [93].

In addition to the reticular formation, another part of the brain, hypothalamus, is also considered as a key regulator of sleep and wakefulness [52, 87]. It has been found that hypocretin-containing cell bodies are exclusively located in the lateral hypothalamus, and hypocretin has been considered to play a critical role in the control of sleepiness and wakefulness [52]. A sleep disorder, human narcolepsy, is caused by deficient hypocretin neurotransmission in the hypothalamus [87].

In Chapter 5, we will review the regulation of the sleep-wake cycle and introduce the motor system of human to set up our experimental hypothesis.

3.1.4 Age Effect in Sleep-Wake Cycle

The relative proportions of each 24-hour day that are devoted to wake, REM sleep, and NREM sleep change dramatically over our lifetime [48]. An infant born at full term sleeps for 16 to 17 hours a day. Twelve to fifteen years later at sexual maturity, an individual sleeps for only about 8 hours. Young adults (Age 18 to 30) enter the life-long downhill course of declining sleep length and depth without recognizing it. Most people first perceive a shallowing and shortening of sleep in the early middle age of 30 to 45. In the late middle age of 45 to 60, people tend to go to bed earlier and to b e much more susceptible to sleep deprivation.

However, the relative PVT (psychomotor vigilance task) performance decrements after 40 hour sleep deprivation is significantly less pronounced in the elderly than in the young, so that both age groups exhibited similar performance decrements after 16 hour into the sleep-deprivation protocol [14].

3.2 What is Drowsiness?

So far, we have reviewed the mechanism and characteristics of the sleep-wake cycle. However, drowsiness has not been clearly defined or characterized in the previous section. Whereas it is relatively clear to distinguish between being wide-awake and definite sleep, drowsy state is *different* from sleep and is *not* fully-awake state either. Indeed, drowsiness varies intermediately between states of partial wakefulness and partial sleep. Besides, every individual has his/her own way to perceive drowsiness, whether it is noticeable or not.

Usually, drowsiness is defined in terms of eye movements and EEG rhythms [97, 114]. Utilizing the EEG signals, the onset of drowsiness can be characterized by a gradual or brisk " alpha dropout " for the adult and by greater amounts of slow activity mingling with the posterior alpha rhythm in childhood [97]. However, in case

Table 3.2: The Epworth Sleepiness Scale (ESS) [28]

0 = no chance of dozing
1 = slight chance of dozing
2 = moderate chance of dozing
3 = high chance of dozing

SITUATION	CHANCE OF DOZING
Sitting and reading	—
Watching TV	—
Sitting inactive in a public place (e.g. a theater or a meeting)	—
As a passenger in a car for an hour without a break	—
Lying down to rest in the afternoon when circumstances permit	—
Sitting and talking to someone	—
Sitting quietly after a lunch without alcohol	—
In a car, while stopped for a few minutes in a traffic	—

we cannot use the EEG sensor, the characterization or the definition is no longer effective.

In our study, *drowsiness*, also referred to as sleepiness, is defined as a spectrum of transient states between wide-awake and definitely-asleep, which is the result of both the circadian rhythm and the sleep need due to the homeostasis. (Refer section 3.1.1). Some of the performance effects resulting from sleepiness can occur without microsleeps [32]. This implies that the belief that only falling asleep while driving will cause a fatigue-related accident is inaccurate [30]. Thus, our definition of drowsiness captures this concern as well.

Drowsiness usually accompanies impaired awareness or vigilance. Sometimes human can recognize if they are in drowsiness state, but sometimes they can not. It is believed that drowsiness is not directly detectable but can only be inferred from the available observation [54]. EEG or EOG (electrooculogram) signals can be used for defining drowsiness [97, 114], but our study does not rely on physiological signals. In the following section, we will review terms related to drowsiness such as fatigue, inattention, boredom, etc.

Related Terminologies

Sleepiness, drowsiness, sleep onset, fatigue, loss of vigilance, inattention, and boredom are the most common terminologies we can find in many relevant literatures. They are "everyday word" we use without rigorous definitions, and each person may have his/her own meaning for each term. For clarification, numerous definitions which can be found from diverse literatures are listed below for each term.

Fatigue Subjective reports of loss of desire or ability to continue performing [133], feeling of tiredness or weariness usually associated with performance decrements [120], consequence of physical labor or prolonged experience and is defined as a disinclination to continue the task at hand [122]. a generic term used to encompass a range of experiences described as anything from 'sleepy,' 'tired,' or 'exhausted' to 'beat' [92], a complex state characterized by a lack of alertness and reduced mental and physical performance [1], usually seen as a gradual and cumulative process due to sustained activity and associated with a disinclination towards effort, eventually resulting in reduced performance efficiency [98], weariness of exhaustion from labour, exertion, or stress [113], fatigue is related to much more than just the time on a task, duration and quality of sleep, shiftwork and work schedule, circadian rhythms, and time of day may affect fatigue [95], a growing longer lasting limitation of a driver's capability [106]. (Although sleepiness has more precise definition than fatigue, fatigue is widely used throughout government, industry, labour, and the public to indicate the effects of working too long, or following too little rest, and inability to sustain a certain level of performance on a task [30].)

Subjective sleepiness Subjective reports of sleepiness or the desire of sleep inattention [114, 133], difficulty in maintaining the wakeful state so that the individual keep asleep if not actively kept aroused. Not a simple feeling of physical tiredness or listlessness [120].

Vigilance State of high efficiency [114], state of readiness in detecting and responding to short lived and randomly occurring changes in the environment [114].

Table 3.3: The Karolinska Sleepiness Scale (KSS) [4, 69]

Karolinska Sleepiness Scale
1 - extremely alert
2
3 - alert
4
5 - neither alert nor sleepy
6
7 - sleepy-but no difficulty in remaining awake
8
9 - extremely sleepy, fighting sleep

(Sustained attention is more commonly used in current psychophysiology [114])

Impairment of vigilance A diminished state of readiness to react [113]

Attention Have been replaced by the term of vigilance [114]

Inattention A short term incapability to react to traffic demands [106]

Sleep onset Transition from wake to sleep, normally into NREM stage 1 [120], states between wide awakeness and definite sleep [65]

Sleepiness A difficulty in remaining awake [28], resulting from the neurobiological process regulating circadian rhythms and the drive to sleep [30], inclination to fall asleep [113].

Alertness Selective attention, vigilance, and attentional control [133].

Assessment of Sleepiness

Subjective Self-Assessment Due to the nature of drowsiness, subjective assessment on drowsiness or sleepiness should be addressed. Though no strong association exists between perceived and actual drowsiness [7], it is important as well how subjects *feel* or *perceive* their own states. Three commonly-used subjective self-assessment sleepiness scales are listed below.

Table 3.4: The Stanford Sleepiness Scale (SSS) [28]

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	×

The Epworth Sleepiness Scale (ESS), which is shown in Table 3.2, is a simple, self-administered questionnaire used to assess subject-perceived levels of sleepiness [28, 113] over the past week or two. The Karolinska Sleepiness Scale (KSS) shown in Table 3.3 is a Likert-type rating scale [4, 113] and is commonly used to measure levels of sleepiness. The Stanford Sleepiness Scale (SSS), like KSS, asks a person about his/her tendency, intention, or potential for falling asleep at a particular moment [28, 113], which is described in Table 3.4.

Objective Assessment It is true that falling asleep is not voluntary but there exist some tests that measure how long it takes to fall asleep or to be awakened when subjects try to do so. Multiple Sleep Latency Test (MSLT) measures how quickly a subject falls asleep, when asked to do so, or lying down in a quiet and darkened bedroom. It is performed under scrutiny with electrodes and wires attached so that sleep can be monitored accurately [13, 34, 55]. In the maintenance of wakefulness test (MWT), a subject sits in bed, resting against pillows in a quiet dimly lit room, attempting to stay awake for 20 (for sometimes 40) min, with the same scrutiny and with the same electrodes attached as in the MSLT [10, 13, 55]. The Oxford Sleep Resistance Test (OSLER) is simply the response to light; if a subject does not respond to light within a predetermined time he/she is judged to fall asleep [113].

Chapter 4

Driver-Vehicle Systems

In this Chapter we study general properties of driver-vehicle systems, covering the structure of driver-vehicle systems, input modality of drivers, interface between drivers and vehicles, and simplified vehicle dynamics. In conjunction with Chapter 3, this Chapter provides a basis for human-in-the-loop experiments dealt within Chapter 5.

4.1 Understanding Driving

While driving, we are not simply looking ahead or around, or accelerating or braking, or steering right or left, but usually performing each of these action concurrently, as a part of some larger task , such as following another vehicle or turning a corner. Indeed, one of the difficulties in understanding driving is that so many relatively complex activities must be performed together in order to achieve what seems to be relatively trivial driving tasks [45].

4.2 Inputs to Driver-Vehicle Systems

Human utilize various sensory systems when they drive. They assess the distance between themselves and other objects, estimate the speed at which both are traveling, listen to engine noise, feel the condition of road surface, etc. We investigate visual, vestibular, auditory, and tactile sensory systems which are essential for driving.

4.2.1 Visual Inputs

For the purpose of understanding driver-vehicle systems, it is sufficient to review two visual systems; one for determining *where* things are and the other for recognizing *what* is present. The first system, the ambient system, makes use of the peripheral as well as the central visual field and is principally concerned with detecting the motion of large objects in the field or of self-motion with respect to the visual environment. Orientation judgments from the visual field using the ambient system employ such natural cues as parallax and perspective. The second system, the focal system, relies primarily on discrimination of fine detail in the central visual field and other cues that lead to appreciation of an object's size and character [131].

Humans navigate and manipulate in a three dimensional (3-D) world, and we usually do so quite accurately and automatically. In order to judge our distance from objects (and the distance between objects) in 3-D space, we rely on a host of *depth cues* to inform us of how far things are away. The three cues used for judging distance, slant, and speed for objects that are within a few meters from an observer are accommodation, binocular convergence, and binocular disparity. The important pictorial cues for judgment of depth and distance for more distant objects and surfaces are linear perspective, relative size, interposition, light and shading, textural gradients, and relative motion (motion parallax) [140].

4.2.2 Vestibular Inputs

The importance of manually controlling the vestibular senses - the semicircular canals for rotational acceleration, and the otolith organs for translational acceleration- are not commonly appreciated [118]. Controlling an automobile or an aircraft simulator without motion cues typically yields evidence for under-damping, e.g., overshoot of step responses, and test subjects complain that the simulator lacks in reality. It has been found that the addition of roll-motion cues to visual cues permits an operator to increase his/her phase lead at frequencies of about 3 rad/sec, thus allowing an increase in gain for the same phase margin and a concomitant reduction in tracking error [118].

Located deep within the inner ear are two sets of receptors, located in the semicircular canals and in the vestibular sacs. These receptors convey information to the brain regarding the angular and linear accelerations of the body, respectively. Thus, when we turn our heads with our eyes shut, we *know* that we are turning, not only because kinesthetic feedback from our necks tell us so but also because there is an angular acceleration experienced by the semicircular canals. Because the head can rotate in three axes, there are three semicircular canals assigned to each axis. Correspondingly, the vestibular sac (along with the tactile sense from the seat of the pants) inform passengers or drivers of linear acceleration or braking in a car. Their organs also provide the constant information about the accelerative force of gravity downward, and hence they are continuously used to maintain our sense of balance (knowing which way is up, and correcting for departures) [140].

Not surprisingly, the vestibular senses are the most important for human system interaction when the systems either move directly (as vehicles) or *simulate* motion (as vehicle simulators or virtual environments). The vestibular senses play two important (and potentially negative) roles here, related to *illusions* and to *motion sickness.*

Vestibular illusions of motion occur because certain vehicles, particularly aircraft, place the passenger in situations of sustained acceleration and nonvertical orientation for which the human body was not naturally adapted. Hence, for example, when the pilot is flying in the clouds without sight of the ground or horizon, the vestibular senses may sometimes be tricked into thinking that up is in a different direction from where it really is. This illusion presents some real dangers of spatial disorientation and the possible loss of aircraft control.

The vestibular senses also play a key role in motion sickness. Normally, our visual and vestibular senses convey compatible and redundant information to the brain regarding how we are oriented and how we are moving. However, there are certain circumstances in which channels become decoupled so that one sense tells the brain one thing and the other tells it something else. There are conditions that cause motion sickness. One example of this decoupling occurs when the vestibular cues signal motion and the visual world does not. When riding in a vehicle with no view of the outside world (e.g,the ship passenger below decks with the portholes closed, or the aircraft passenger flying in the clouds), the visual view forward, which is typically framed by a man-made rectangular structure, provides no visual evidence of movement (or evidence of where the true horizon is). In contrast, the continuous rocking, rolling, or swaying of the vehicle provides very direct stimulation of movement to the vestibular senses. When the two senses are in conflict like this, motion sickness often follows.

Conflict between the two senses can also result from the opposite pattern. The visual system can often experience a very compelling sense of motion in video games, driving or flight simulators, and virtual environments, even when there is no motion of the platform whatsoever. Here again happens a conflict, and there exists a real danger of a loss of function (or wasted experience) when the brain is distracted by the unpleasant sensations of motion sickness.

4.2.3 Auditory Inputs

The automobile driver uses auditory cues to maintain vehicle speed. Drivers who are masked their ears on a vacant highway found themselves driving a speed far higher than they intend [118]. The stimulus for hearing is sound, resulting from vibrations (compression and rarefaction) of air molecules. The ear is the sensory transducer and has three primary components that are responsible for differences in our hearing experiences. The pinnea serves to collect sound and detect where it comes from thanks to its asymmetrical shape. Mechanisms of the outer and middle ear (the ear drum or tympanic membrane, the hammer, anvil, and stirrup bones) conduct and amplify sound waves into the inner ear and are potential sources of breakdown or deafness. The muscles of the inner ear are responsive to very loud noises and will reflexively contract to attenuate the amplitude of vibration before its conveyance to the inner ear [140]

4.2.4 Tactile Inputs

Lying just under the skin are sensory receptors that respond to pressure on the skin, they relay their information to the brain regarding the subtle changes in force applied by the hands and fingers as they interact with objects in the environment. We can see the importance of these sensory channel in two very different controls by pilots: the landing gear and the flaps [140]. Drivers usually can judge road surface conditions based on their feeling from steering wheels.

4.3 Interface of Driver-Vehicle Systems

4.3.1 Steering Control

There is no definite functional relationship between the turning angle of the steering wheel made by the driver and the change in driving direction, because of the correlation of turns of the steering wheel, alteration of steer angle at the front wheels, development of lateral tire forces, and alteration of driving direction. Standard steering system is not linear because of the elastic compliance with the chassis components.

In order to move a vehicle, the driver must continually adjust themselves to the relationship between turning the steering wheel and altering the direction of the vehicle. The driver will monitor a wealth of information, going far beyond the visual perceptive faculty (visible from the desired direction). These factors would include, for example, the roll inclination of the body, the feeling of being held steady in the seat (transverse acceleration) and the self-righting torque the driver will feel through the steering wheel. It is therefore the job of the steering system to convert the steering wheel angle into as clear a relationship as possible to the steering angle of the wheels and to convey feedback the vehicle's state of movement to the steering wheel [105].

4.3.2 Throttle/Brake Control

4.4 Simplified Vehicle Dynamics

4.4.1 Lateral Dynamics

A two-degree of freedom model, commonly referred to as the Bicycle Model, encompasses the dominant dynamics of the vehicle under normal operation [78, 104]. Emergency maneuvers and abrupt changes in velocity are not considered in this model. Advanced vehicle models are available in numerous literatures [78, 104, 105].

The states we consider are yaw rate $\dot{\psi}$ and lateral velocity v. The state space representation is given by

$$\dot{x} = Ax + Bu \tag{4.1}$$

where

$$x = \begin{bmatrix} v \\ \dot{\psi} \end{bmatrix}, \quad A = \begin{bmatrix} \dfrac{-2(C_{\alpha f} + C_{\alpha r})}{mU} & \dfrac{2(C_{\alpha r}b + C_{\alpha f}a)}{mU} \\ \dfrac{2(C_{\alpha r}b + C_{\alpha r}a)}{I_z U} & \dfrac{-2(C_{\alpha f}a^2 + C_{\alpha r}b^2)}{I_z U} \end{bmatrix}$$
$$u = \begin{bmatrix} \delta_f \\ \delta r \end{bmatrix}, \quad B = \begin{bmatrix} \dfrac{2}{m}C_{\alpha f} & \dfrac{2}{m}C_{\alpha r} \\ \dfrac{2aC_{\alpha f}}{I_z} & -\dfrac{2bC_{\alpha r}}{I_z} \end{bmatrix} \tag{4.2}$$

here m = vehicle mass, a = distance from front wheels to CG (center of gravity), b = distance from rear wheels to CG, I_z = polar moment of inertia, $C_{\alpha f}$ = front cornering stiffness, $C_{\alpha r}$ = rear cornering stiffness, U = longitudinal velocity, δ_f = front steering wheel angle, and δ_r = rear steering wheel angle. Common numerical values of the associated coefficients can be found in [15, 78].

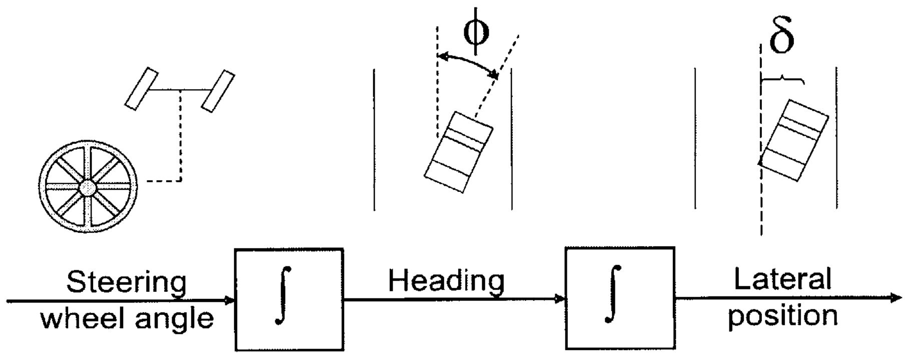

Figure 4-1: An example of a hierarchical control system: automobile driving [141]

Multiaxis Control

A driver must often perform more than one tracking task simultaneously. He/She may steer, while simultaneously controlling speed, to execute a passing maneuver. Multiaxis systems can be distinguished in two ways: a system with two variables to be controlled as well as their inputs are essentially independent of one another; and a system with cross-coupling so that the state of the system or variable on one axis partially constrains or determines the state of the other. An example of two basically independent axes is that when a driver controls speed, it has a minor effect on the lateral (steering) handling characteristics of the vehicle. In contrast, the heading and lateral position of an automobile are highly cross-coupled, because a vehicle heading directly affects its lateral position. In this case, the two cross-coupled tasks are considered to be hierarchical. That is, lateral position cannot be changed independently of heading control. The steering wheel, which directly controls headings, is used to obtain a change in lateral position [141].

4.4.2 Longitudinal Dynamics

Consider a vehicle moving on inclined road. The external longitudinal forces acting on the vehicle include aerodynamic drag, gravity, longitudinal tire forces, and rolling resistance forces. These forces are described in detail in [103].

The state space representation is given by

$$m\ddot{x} = F_{xf} + F_{xr} - F_{aero} - R_{xf} - R_{xr} - mg\sin\theta \tag{4.3}$$

where F_{xf} is the longitudinal tire force at the front tires, F_{xr} is the longitudinal tire force at the rear tires, F_{aero} is the equivalent longitudinal aerodynamic drag, R_{xf} is the force due to rolling resistance at the front tires, R_{xr} is the force due to rolling resistance at the rear tires, m is the mass of the vehicle, g is the acceleration due to gravity, and θ is the angle of inclination of the road on which the vehicle is traveling. The angle θ is defined to be positive clockwise when the longitudinal direction of motion x is toward the left.

The control of longitudinal vehicle motion has been pursued at many different levels. Common systems involving longitudinal control available on today's passenger cars include cruise control, anti-lock brake systems, and traction control systems. Other advanced longitudinal control systems include radar-based collision avoidance systems and adaptive cruise control systems [103].

Chapter 5

Simulator-based Human-in-the-Loop Experiments

This chapter covers human-in-the-loop experiments using a fixed-based driving simulator. We describe: 1) experimental objectives, 2) design of experiment including hypothesis and independent/dependent variables, 3) detailed hardware and software setup, and 4) experiment procedures.

5.1 Experimental Objectives

The simulator-based human-in-the-loop experiments are intended to explore the characteristics of drowsy driving. As is mentioned in Chapter 1, drowsy driver detection problems should consider both vehicle and human components of transportation accidents. The proposed experiments focus on human perspective of the problem. Mainly, differences in driver performance under different sleep-deprivation levels are examined. Both common driving tasks and some non-driving tasks such as psychomotor vigilance tasks are given to each driver.

The purpose of this experiment does not lie in proposing another drowsiness monitoring technique, but in understanding in-depth characteristics of driver-vehicle systems under different sleep-deprivation levels of drivers. For instance, we will not only compare driver performances in stimulus-response tasks between non sleep-deprived and partially sleep-deprived groups, but also investigate tasks which show little performance deterioration under sleep deprivation. Although explicit sleep-onset episodes often cause the most serious performance failures, some performance effects resulting from sleepiness can occur without microsleeps [30, 32]. This suggests that the popular belief should be corrected that only a fall-asleep-driver causes a fatigue-related accident. There are moments a driver still looks awake (eyes wide open) but does not process any information. These *looking without seeing* moments are dangerous and need to be captured by an effective system [106]. Moreover, we will study how drowsy driving affects attentiveness, rapidity, and accuracy of actions. Although it has been found that attentiveness and rapidity suffer more than accuracy under sleep deprivation in normal life [65, 138, 139], there has been little comparable analysis in driving situations.

We expect the experimental results to disclose the characteristics of drowsy driving, and to enable us to design a proper drowsy driver detection system and the associated counter-measures. The in-depth analysis will lead us to a more systematic way to drowsy-driver detection.

5.2 Experimental Methods

5.2.1 Experimental Hypotheses

In this experiment, our main working hypothesis is that the deterioration degree of drowsy driver performance is greater in 'high-level' decision-making tasks that demand human motor functions involving the basal ganglia than in 'lower-level' regulation tasks involving the cerebellum. The rationale of this hypothesis lies in the physiological basis of the sleep-wake cycle and the motor control of human nervous system.

We first examine the role of the basal ganglia and the cerebellum in the motor system. The motor control of human nervous system is shown in Fig. 5-1 [60], which shows the control flow of our motions or movements. As we first receive some external signals, they are fed into the spinal cord and the brain stem, which integrate the

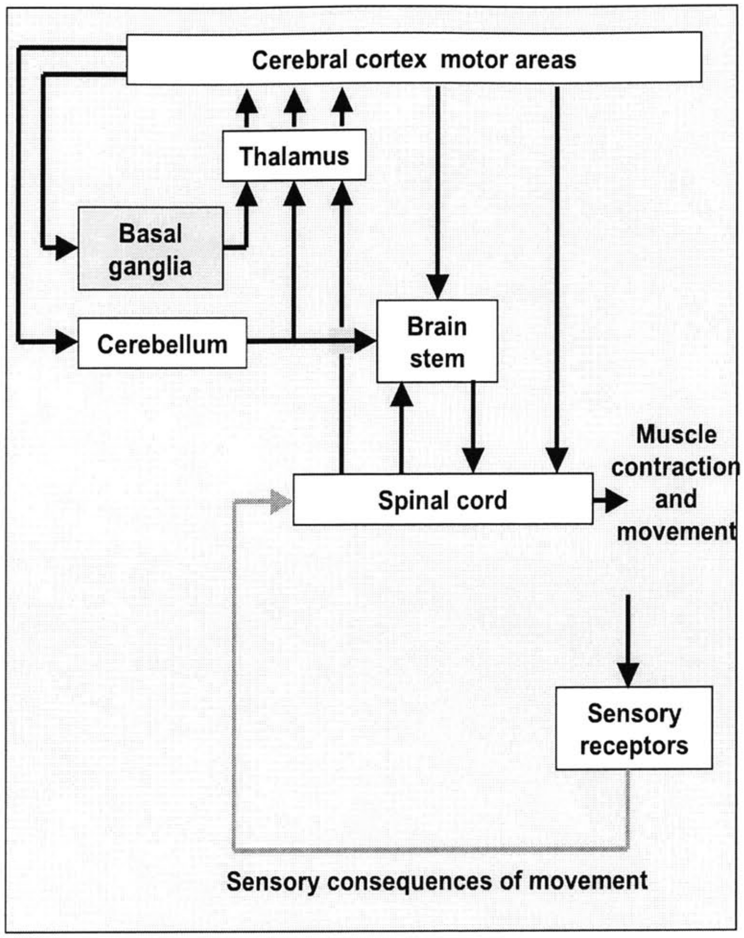

Figure 5-1: Motor control of human nervous system [60]

information to send to the upper level of motor system, the cerebral motor cortex area [17, 60, 85]. The basal ganglia receive inputs from the cortical areas, which are in charge of decision making or switching between tasks. It has been known that the basal ganglia supervise human decisions on what kind of tasks human are going to do. Once the basal ganglia and the associated cerebral motor cortex area decide what to do, the next control level involves the cerebellum, whose function is to improve the accuracy of movements by comparing motor commands with information on the resultant motor actions. For examples, the cerebellum controls general tracking tasks, such as lane tracking while driving.

Roughly speaking, the basal ganglia play an important role in generating sequential movements and triggering transitions of different brain states; the cerebellum influences the motor systems by adjusting the motor commands while a movement is in progress as well as during repetitions of the same movements. For example, it requires considerable basal ganglionic functions for a driver to switch lanes in an attempt to be away from an aggressive vehicle while it relies on the cerebellum function to cruise on a moderately curvy road. The activities concerned with learning how to drive a new vehicle may involve both.

Now, recall the brain parts controlling the sleep-wake cycle in Chapter 3. We have reviewed that the hypothalamus and the reticular formation are the regulators of the sleep-wake cycle. The hypothalamus is located in the middle part of the brain, mainly controlling the sleep-wake cycle and body temperature. The reticular formation is located in the brain stem and is known to generate the neurotransmitter to regulate the sleep-wake cycle.

As it turns out, the reticular formation and the hypothalamus have more influence on the basal ganglia than on the cerebellum. The reticular formation is responsible for the production of the main neurotransmitters involved in sleep and wakefulness. These neurotransmitters primarily play an excitatory role in the activation and arousal of the associated brain areas. Cells releasing these neurotransmitters project into the cerebral cortex and forebrain including the basal ganglia, but not into the cerebellum. During sleep or drowsiness, the activities of the neurotransmitter to release cells decrease, and thus the concentration levels of the above neurotransmitters in the basal ganglia and other cortical areas are affected to a greater extent than in the cerebellum. Some neuroanatomical studies [87] of the hypocretin system show that hypocretin may have more influences on the prefrontal areas of the brain than on the lower movement control system including the cerebellum.

Given the above arguments, it is reasonable to examine if the motor functions involving the basal ganglia deteriorate more than those involving the cerebellum during drowsiness. Recent studies [20, 132, 145] tried to find a mapping between driving tasks and areas of brain activations by using imaging techniques such as fMRI (Functional Magnetic Resonance Imaging). They examined the activated brain areas of a subject under a variety of simulated driving circumstances. It is beyond the scope of this thesis to find the exact mapping between brain areas and driving tasks for various sleep levels.

We study several driving tasks and secondary tasks that have different nature or characteristics, trying to find out if there exist some tasks that are more vulnerable to drowsiness than others. Showing how *task type* and *sleep-deprivation level* affect driving performances, this approach would provide a design strategy for building drowsiness-detection devices.

At this point, it is important to discuss some of the experiments performed on humans and other animals involving sleep deprivation. In a study with human subjects Dinges and Kribbs [32] discovered that performance on shorter tasks is not impaired when individuals are sleep deprived; however, performance on longer tasks which require sustained attention becomes impaired. In other experiments subjects report perceptual distortions or even hallucinations [40]. Rechtschaffen's study on rats that were sleep deprived between 5 to 33 days showed severer effects; they began to look sick, stopped grooming themselves, and became weak and uncoordinated. Some of them died and some had to be sacrificed. On autopsy, enlarged adrenal glands, stomach ulcers, and fluid in lungs were found; note that these are the typical signs of stress [22].

Cerebral function is more profoundly impaired by sleep deprivation than in the functions of any other organ or part of the brain [50].

5.2.2 Independent Variables

The independent variable of the experiment is the *sleep-deprivation level* of subjects, i.e., the different levels of homeostatic need for sleep. We consider subject groups with two different sleep-deprivation levels, "partial sleep-deprivation" and "no sleep-deprivation."

The level of sleep deprivation is determined by the amount of sleep each subject have before the test day. The non-sleep-deprived group consists of subjects who have been sleeping at least 7 to 8 per 24 hours for more than a week before the test day. The partially-sleep-deprived group consists of subjects who have had less than 7 hours in bed two days before the test and less than 4 hours in bed on the eve of the test.

Figure 5-2: Actiwatch AW-16

As is explained in Chapter 3, there is no direct way to control a driver's vigilance level without using drugs [122]. Thus, we control the "causes" of sleep to maximize or minimize the probabilities of entering the drowsiness state. The non-sleep-deprived group is scheduled to have experiments only between 9:00 am to 12:00 pm, whereas partially-sleep-deprived group is scheduled between 2:00 pm to 4:00 pm. Such an arrangement takes into account the wake-drowsy peaks of the circadian rhythm.

Actiwatches, small actigraphy-based data loggers that record digitally integrated measure of gross motor activities [88], allow us to measure the amount and quality of sleep for several days prior to the experiments. Subjects are asked to wear the Actiwatch, which can be worn just like a watch, for one week prior to the non-sleep-deprived session and for 2-3 days prior to the partially-sleep-deprived session. Fig. 5-2 shows the Actiwatch AW-16 used in the experiment. It is 16 grams, 28 $\times$ 27 $\times$ 10 mm, waterproof, and has 16 kbytes memory.

5.2.3 Task Definitions

For both non-sleep-deprived and partially-sleep-deprived subjects, a series of driving and non-driving tasks are given to drivers during simulated driving environment, which are described below.

Tracking Tasks

Five different tracking tasks are given to each subject in a random order while driving. These are categorized such, as drivers are expected to drive in the simulator as if they were driving in real world and were not supposed to change lanes or pass a lead vehicle in front of them. Depending on each scenario, drivers face a straight road without

Figure 5-3: Screen shot of Curved Lane Tracking.

any disturbance, straight road with disturbances such as wind gusts, straight road with a lead vehicle, straight road with changes in steering dynamics, or curvy road. Definitions of each scenario given to subjects are summarized as follows.

Curved Lane Tracking (CL) A curved roadway is presented during the experiment. Drivers are supposed to keep the car centered in a serpentine road under a specified speed range between 80 and 100 kph. The length of each serpentine is approximately 1500m. Each test includes three CL events. Fig. 5-3 is a screen shot from the driving simulator that shows a part of a serpentine. Its geometry can be found in Appendix A.1. Subject drivers practice on a curvy road before they start the main experiment. The serpentine geometry used in the practice is different from that in the main experiment.

Straight Lane Tracking given Changes of Steering Characteristics (CS) Drivers are supposed to keep the vehicle centered in the straight road and to maintain a specified speed range between 80 and 100 kph, while the original steering dynamics are altered. Each test includes three CS events, each of whose length is 1900m.

We introduce some nonlinearities to the steering alignment system which is originally modeled as a linear system. We can easily apply external or environmental disturbances such as wind gust, bumpy roads, fogs, etc. However, we are not able

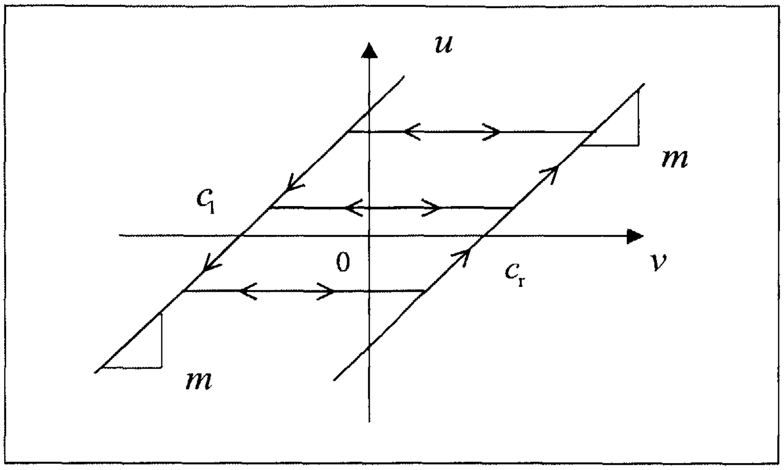

Figure 5-4: Backlash [125]

to control the presence of environmental disturbances in driving situation. The CS are intended to observe how drivers adapt themselves to external disturbances and to study how to apply this event to real-driving situations. Thus, we introduce backlash in the steering dynamics as one of the nonlinearities or changes in steering dynamics.

Backlash is a common nonlinearity that limits the performance of speed and position control. It causes a phase delay, and thus a loss of information by chopping the peaks of input signals [125]. The discrete-time version of the backlash model is

$$u(t) = B(\nu(t)) = \begin{cases} m(\nu(t) - c_l) & \text{if} \quad \nu(t) \leq \nu_l \\ m(\nu(t) - c_r) & \text{if} \quad \nu(t) \geq \nu_r \\ u(t-1) & \text{if} \quad \nu_l < \nu(t) < \nu_r \end{cases} \tag{5.1}$$

where, $\nu_l = \frac{u(t-1)}{m} + c_l$, $\nu_r = \frac{u(t-1)}{m} + c_r$. Coefficients used in the simulation are $m = 1$, $c_l = -10\,\text{deg}$, and $c_r = 10\,\text{deg}$. Fig. 5-4 describes the backlash model [125].

Straight Lane Tracking given a Lead Vehicle (LV) When a lead vehicle appears traveling with small speed variation, subject drivers are supposed to follow the vehicle with safe margin they choose. Before the main experiment starts, drivers are told not to pass their lead vehicle. Each test includes three LV events and each lead vehicle presents for 100 seconds. A speed variation profile of a lead vehicle is included in Appendix A.1. Fig. 5-5 is a screen shot of the driving simulator that shows a lead

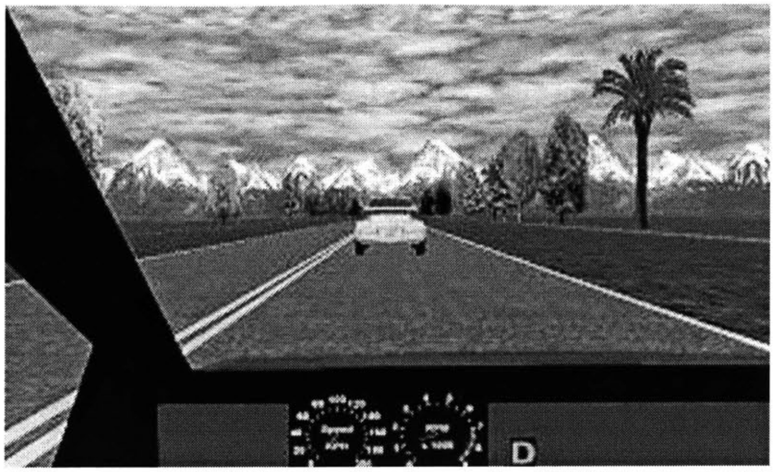

Figure 5-5: Screen shot of Straight Lane Tracking given a Lead Vehicle

vehicle.

Straight Lane Tracking (LT) Drivers are supposed to keep their vehicle centered in straight road under a specified speed range between 80 and 100 kph. Without any disturbances or stimuli present, a 700m - long straight roadway is introduced. Each test includes three LT events.

Straight Lane Tracking given Wind Gusts (WG) Some external pseudo-random disturbances are introduced during the experiment. Drivers are supposed to keep their vehicle centered in straight road under a specified speed range between 80 and 100 kph. Well defined multiple sine waves specify the pseudo-random disturbances [109]. Each test includes three WG events, each of which lasts for 24 seconds. Details of the disturbance model are shown in Appendix A.1.

Stimulus-Response Tasks

We have four different stimulus-response tasks given to each subject in a random order during simulated driving. Stimulus can be an auditory ringing signal, a visual red triangular symbol, or an over-head lane change sign on the driving lane. They can be either critical or negligible in terms of safe driving. Definitions of the four stimulus-response tasks are given as follows.

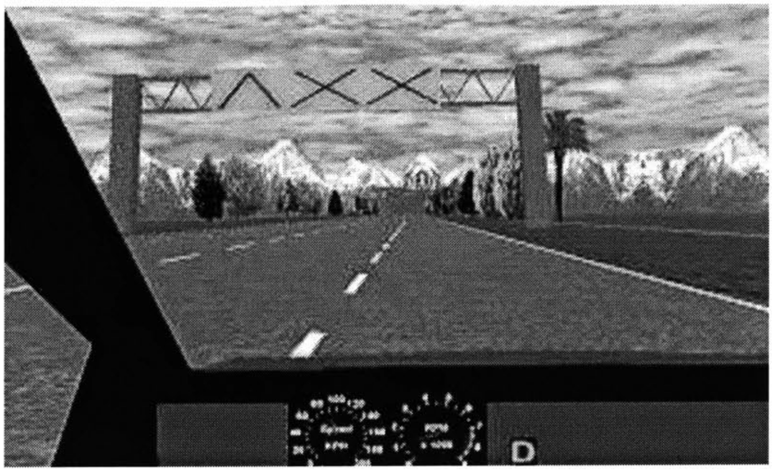

Figure 5-6: Screen shot of Double Lane Change Task.

Single Lane Change Task (SLCT) Once an overhead lane change sign appears, drivers are supposed to change lanes immediately. Each lane change sign has an array consisting of an arrow and two X's. The arrow indicates the target lane that drivers need to move into. The rest of the lanes are marked with Xs to indicate that drivers should not move in those lanes. SLCT sign refers to the moment when the lane indicated by the arrow is adjacent to the current driving lane. Each experimental session includes five SLCT events.

Double Lane Change Task (DLCT) Once an overhead lane change sign appears, drivers are supposed to change lanes immediately. The lane change sign has a similar format as described in SLCT. However, DLCT sign refers to the moment when the lane indicated by the arrow is separated from another lane, and drivers are supposed to shift two lanes at once. Fig. 5-6 is a screen shot of the driving simulator that shows one of the lane change signs. Each experimental session includes five DLCT events.

Auditory Psychomotor Vigilance Task (APVT) Drivers are supposed to press a green button on the steering wheel immediately after hearing a ringing tone. The ringing tone lasts for about 1 second. Each experimental session includes ten APVT events.

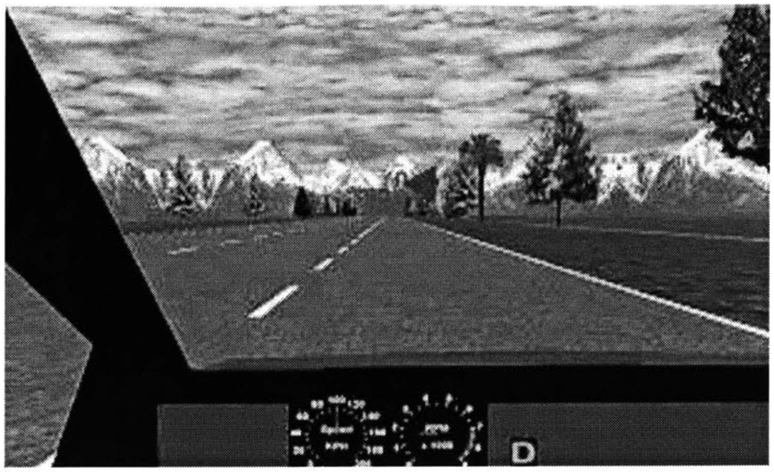

Figure 5-7: Screen shot of Visual Psychomotor Vigilance Task.

Visual Psychomotor Vigilance Task (VPVT) Drivers are supposed to press a green button on the steering wheel immediately after recognizing a red stimulus on the screen. The stimulus is shown for 5 seconds if there is no response from subjects. Each experimental session includes ten VPVT events. Fig. 5-7 is a screen shot of the driving simulator that shows the red stimuli.

Emergency Maneuver (EM) Drivers are supposed to avoid a collision when a vehicle ahead suddenly stops. Drivers are free to choose to brake or to steer away or to do both. This task is intended to examine drivers' response to an emergent situation. EM is presented as the last element of the experiment due to high collision risk. (If an experimental session is resumed after an accident, we need to cope with the simulation fidelity issue.)

Table 5.1 shows the full list of tasks defined previously. Instead of grouping the simulated tasks into tracking tasks and stimulus-response tasks, we can consider CL, LV, LT, WG, and SLCT as examples of common driving tasks, as opposed to CS, DLCT, APVT, VPVT, and EM as non-common driving tasks. Their characteristics will be investigated in Chapter 6.

Table 5.1: Simulated Tasks

Accronym	Tasks
CL	Curved Lane Tracking
CS	Straight Lane Tracking given Changes of Steering Dynamics
LV	Straight Lane Tracking given a Lead Vehicle
LT	Straight Lane Tracking
WG	Straight Lane Tracking given Wind Gusts
SLCT	Single Lane Change Task
DLCT	Double Lane Change Task
APVT	Auditory Psychomotor Vigilance Task
VPVT	Visual Psychomotor Vigilance Task
EM	Emergency Maneuver

5.2.4 Dependent Variables

The dependent variables of this experiment are the *performance measures* of each simulated task. Using driver-vehicle data collected during the experiment, we employ the following metrics to assess driver performance for the corresponding tasks. A list of raw data collected during the experiment are presented in Appendix A.1.

Performance Measures for Tracking Tasks

Root Mean Square Error with Threshold (RMT) RMT is a parameterized variation of the conventional Root Mean Square (RMS) error, which is usually used to measure general tracking performance. We have devised RMT instead of RMS to capture common driving characteristics; drivers tend to ignore a certain level of errors, as they generally try to stay *within* the driving lane instead of trying to follow a single line on the road. This driving characteristic is usually called "good-enough" or "satisficing" characteristics of drivers [61]. Thus, we introduce a threshold parameter α to the RMS so that RMT vanishes as long as driving trajectories stay within the threshold α.

RMT is defined as

$$RMT = \sqrt{\frac{\sum_{k=t_0}^{k=t_f} max(|x(k)| - \alpha, 0)^2}{n}} \tag{5.2}$$

where $x(k)$ is the lateral lane position of a driver with respect to the centerline of the driving lane, α is a threshold value varying from 0 to 50% of the road width, n is a number of data within the sampling window, t_0 is the initial time in the sampling window, and t_f is the terminal time in the sampling window. It is apparent that (5.2) is reduced to a typical RMS error, $\sqrt{\frac{\sum x(k)^2}{n}}$, when $\alpha = 0$.

Rate of EXceedance (REX) Another metric for measuring the lane tracking performance is REX, which is based on the *number* or *frequency* of lateral deviations exceeding a threshold. Regardless of the amplitude of deviation, REX gives the same penalty for all deviations exceeding the threshold, and thus captures different properties from RMT. REX is defined as

$$REX = \frac{\sum_{k=t_0}^{k=t_f} 1(|x(k)| - \alpha)}{n} \tag{5.3}$$

where $1(|x(k)| - \alpha) = 1$ when $|x(k)| \geq \alpha$, and $1(|x(k)| - \alpha) = 0$ otherwise.

Effective Time Delay (ETL) The Effective Time Delay (ETL) of continuous tasks can be considered to be equivalent to the Reaction Time (RT) of discrete tasks [140]. The ETL is estimated by applying McRuer's Crossover Model to some continuous tasks. McRuer's Crossover Model claims that, for tracking tasks, human respond in such a way as to make the total open-loop transfer function behave as a first order system with gain and effective time delay [83]. Thus, the total open-loop transfer function can be expressed as

$$Y_H Y_P = \frac{Ke^{-\tau s}}{s} \tag{5.4}$$

where Y_H is human, Y_P is a plant, K is a gain, and τ is an effective time delay (ETL).

Performance Measures for Stimulus-Response Tasks

Reaction Time (RT) Reaction Time (RT) is a measure of how fast a driver reacts to stimuli presented abruptly. Accordingly, RT is defined as

$$RT = t_{action} - t_{stimulus} \tag{5.5}$$

where $t_{stimulus}$ is the time a stimulus is presented to the driver and t_{action} is the time the man-vehicle system reacts to the given stimulus. The unit of RT is milliseconds.

Lapse Rate (LR) A lapse is a metric to measure a driver's inadequate performance when he/she does not respond to a stimulus in a timely manner. For the sustained Psychomotor Vigilance Task, a lapse is defined as a Reaction Time (RT) greater than or equal to 500 ms [34]. On the other hand, when a sustained Psychomotor Vigilance Task is used as a secondary task during simulated driving, a threshold of 600 ms is claimed to be more relevant [69]. In general, a lapse can be defined as a RT greater than or equal to a preset threshold, and the Lapse Rate (LR) can be computed from

$$LR = \frac{\sum_{i=1}^{i=n} 1(RT_i \geq \theta)}{n} \tag{5.6}$$

where n is a total number of RTs under consideration, θ is a lapse threshold, and $1(RT_i \geq \theta) = 1$ when $RT_i \geq \theta$, zero otherwise. The lapse threshold θ may have different values for different types of stimuli (e.g. auditory or visual stimuli) or different types of tasks (e.g. driving or non-driving tasks).

Correct Response Rate (CRR) Accuracy of drivers' response are measured by Correct Response Rate (CRR). It is defined as

$$CRR = \frac{\sum_{i=1}^{i=n} 1(Response_i)}{n} \tag{5.7}$$

where n is the total number of responses under consideration, $1(Response_i) = 1$ when the $Response_i$ is correct, i.e., drivers do what they are supposed or instructed to do so. On the other hand, $1(Response_i) = 0$ when the $Response_i$ is incorrect. CRR measures the accuracy of drivers' response whereas RT and LR measure the speed of drivers' response.

5.2.5 Laboratory Set-Up

We develop a simulation test bed that allows a subject to drive with pre-designed driving scenarios. A simulated driving is programmed and run by STISIM Drive

Figure 5-8: Laboratory setting

v2.06.07. STISIM Drive is a fully interactive Windows PC-based simulator [124]. A built-in programming language, SDL(Scenario Definition Language), enables us to generate driving scenes, road geometry, weather conditions, traffics, dashboard design, stimuli given to the drivers, etc. Visual Basic V6 is used to model steering dynamics change during the experiment.

STISIM Drive runs on a Dell PC–Pentium 4, 2.6 GHz, 512MB of RAM. Logitech MoMo steering wheel and pedal set is connected to the Dell PC, and is recognized as a control device to the STISIM Drive. The steering wheel could be rotated ± 120 degrees. A projector and a wide screen (45 in x 60 in) are implemented in the lab, showing driving scene to a subject. A 6-way power adjustable driver's seat is used for the experiment. Fig. 5-8 shows an image of the lab setting. A detailed seat buck design is provided in Appendix A.4.

Copilot for obtaining PERCLOS (PERcentage of eye CLOSure) value and a series of JPEG images of a driver is installed in Compaq Presario Laptop–Celeron(4), 2.40GHz, 192MB of RAM. The data are collected by LabView 7.0 through a serial port and IMPERX frame grabber.

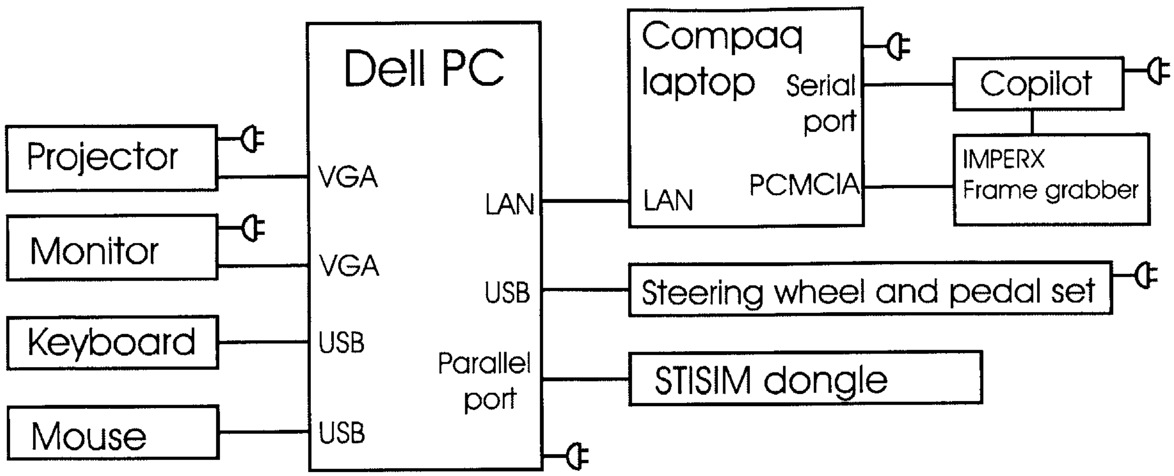

Figure 5-9: Laboratory system flow diagram.

Dell PC and Compaq laptop are connected to each other by a cross cable, which allows NTP (Network Time Protocol) to synchronize the system time of both computers. NTP is installed on both computers; Dell PC and Compaq laptop work as a server and a client, respectively. The lab system flow diagram is shown in Fig. 5-9.

Appendix A.1 includes the detailed scenario programming using SDL of STISIM Drive and Visual Basic.

5.2.6 Experimental Procedure

Control of the Independent Variable

Subjects are asked to wear the Actiwatch all days and nights before the experiment and at the same time, to fill out a sleep diary every day. For non-sleep-deprived conditions, subjects are asked to wear the Actiwatch and to write the sleep diaries for a week before the experiment. For partially-sleep-deprived conditions, subjects wear the Actiwatch and write the sleep diaries at least two days before the experiment. For the specific from of sleep-diary, refer to the Appendix A.2.

Experiment procedure

Each test session lasts for an hour, including a 10 minute demo drive during which a driver learns the tasks described in Section 5.2.3 except WG, CS, and EM. WG, CS, and EM are not included in the demo, as they are not rule-based tasks; but emergency-type ones, for which driver should react with their instinct. Other than those three tasks, an experimenter explains how subjects should drive or react for relevant tasks. Drivers are asked to practice each task until adequate performance level is achieved, and are able to ask any questions regarding tasks and driving simulator.

The above instructional and demonstrational session is followed by the main experiment scenario. During the initial 20,000 m (approximately the first 10 minutes) of the main experiment, no perturbation inputs are present, and a driver is only asked to drive along a straight roadway with a speed range between 80 and 100 kph. This relaxing interval is included as an *unmasking* period in order to remove hyper-vigilance or any factor that prevents the driver from revealing sleepiness. Then, randomly placed and ordered tasks as is described in Section 5.2.3 are given to the driver successively. No tasks are given simultaneously to a driver. The driver is not informed of the time and the duration of the tasks including masking period before or during the main simulation. This part runs for up to 40 min.

An experimenter is present in the laboratory with a subject throughout the whole test session. Conversation between the subject and the experimenter is prohibited during the main scenario unless an emergency occurred. Sleep-deprived subjects are provided with transportation on the test day to avoid safety-related accidents.

5.2.7 Participants

A total of 12 subjects participated in the experiment twice; under conditions of partial sleep-deprivation and no sleep-deprivation. The ages of these subjects ranged from 29 years to 49 years, with an average of 41.7 years and a standard deviation (STD) of 6.4 years. The average amount of sleep these subjects had per day for two weeks prior to the sleep monitoring was 6 hours 42 minutes (STD = 47 minutes). None of the subjects had any serious health problems or were under any medication.

For the non-sleep-deprived condition, subjects had an average of 7 hours 22 minutes (STD = 46 minutes) of sleep per day for 7 days prior to the experiment. For the partially sleep-deprived condition, subjects had 6 hours 11 minutes of sleep on the night two days before the experiment (STD = 35 minutes), and had 3 hours 27

Table 5.2: Experiment order for each subject

Subj. Number	First Experiment	Second Experiment
S01	No sleep-deprivation	Partial sleep-deprivation
S02	Partial sleep-deprivation	No sleep-deprivation
S03	Partial sleep-deprivation	No sleep-deprivation
S04	No sleep-deprivation	Partial sleep-deprivation
S05	No sleep-deprivation	Partial sleep-deprivation
S06	Partial sleep-deprivation	No sleep-deprivation
S07	No sleep-deprivation	Partial sleep-deprivation
S08	Partial sleep-deprivation	No sleep-deprivation
S09	Partial sleep-deprivation	No sleep-deprivation
S10	Partial sleep-deprivation	No sleep-deprivation
S11	No sleep-deprivation	Partial sleep-deprivation
S12	No sleep-deprivation	Partial sleep-deprivation

minutes of sleep on the eve of the experiment (STD = 26 minutes) by average.

The order of the experiment was counterbalanced: one half of the randomly selected subjects completed no sleep-deprivation session prior to the partial sleep-deprivation session, and the other half in a reverse order. No subject yielded a crash during the simulation. Table 5.2 shows the subjects' identification number and the corresponding order of experiments. Detailed subject data are summarized in Appendix A.3

Chapter 6

Analysis of Experimental Data

This Chapter, based on the simulator-based human-in-the-loop experiments set-up presented in Chapter 5, is dedicated to the extensive analysis of experimental data to investigate drowsy driving characteristics. We first analyze with-in subject performance differences between two different sleep-deprivation levels. Then, mainly focusing on subjects' performances in common driving tasks and secondary tasks, we utilize nonparametric statistical tests and McRuer's Crossover Model. Finally, other concerns such as order/learning effects or power analysis follow.

6.1 With-in Subject Performance Analysis

In this section, we study performance differences between two different sleep-deprivation levels for various tasks. We are mainly interested in: which driver-vehicle data show more or earlier differences between two groups?; which data show the least amount of differences?; is there any commonalities in tasks showing performance degradation when drivers are sleep-deprived?; etc.

Each subject has participated in the experiment twice with different sleep-deprivation levels, and this section compares with-in subject performance differences. We use a *nonparametric* statistical test called Wilcoxon Signed Rank Test [71, 72, 121] to determine if there exist significant performance differences between two groups. Most statistical tests need a variety of assumptions about the distribution of the population from which the samples are drawn. Situations arise in practice in which such assumptions may not be justified or doubtful to apply [121]. We use nonparametric tests, as they are *independent* of population distributions and their associated parameters. P-values listed in the following sections are obtained from the Wilcoxon Signed Rank Test, unless otherwise mentioned. The significance level α is set at 0.1, as is conventionally used in general human factor studies.

Chapter 5 describes performance metrics and data from a whole set of driving and non-driving tasks in the experiment. Here we examine APVT (Auditory Psychomotor Vigilance Task), CL (Curved Lane Tracking), DLCT (Double Lane Change Task), EM (Emergency Maneuver), LT (Straight Lane Tracking), LV (Straight Lane Tracking given a Lead Vehicle), SC (Straight Lane Tracking given Changes of Steering Dynamics), SLCT (Single Lane Change Task), VPVT (Visual Psychomotor Vigilance Task), and WG (Straight Lane Tracking given Wind Gusts). We study characteristics of drivers for each performance category; 1) lane-tracking performance, 2) stimulus-response performance, 3) steering and throttle control, 4) lane change tasks in McRuer's Crossover Model framework, and 5) learning effects.

6.1.1 Lane Tracking Performance

Keeping a moving vehicle on a roadway with an appropriate speed is one of the fundamental driving skills. Deterioration in lane tracking performance can lead to overall driving malfunction. Researchers have studied lane tracking performance as a main indicator for detecting drowsy drivers [7, 63, 79, 136]. However, as is shown in Chapter 2, the validity of lane tracking performance as a drowsiness indicator is still controversial. Moreover, between alert and drowsy drivers, there has been little studies on lane tracking performance for various road or weather conditions. This type of study is nontrivial, as real driving happens under a dynamic situation, i.e., under a variety of different environmental situations. Thus, for non-sleep-deprived and partially-sleep-deprived groups, we examine lateral lane tracking performance under several different conditions to see drivers' ability to maneuver a vehicle inside the road way.

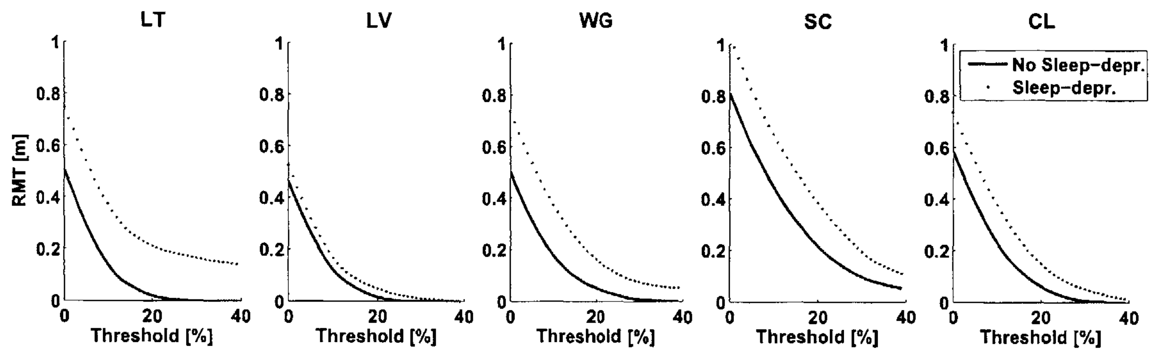

Figure 6-1: RMT sampled over 350m

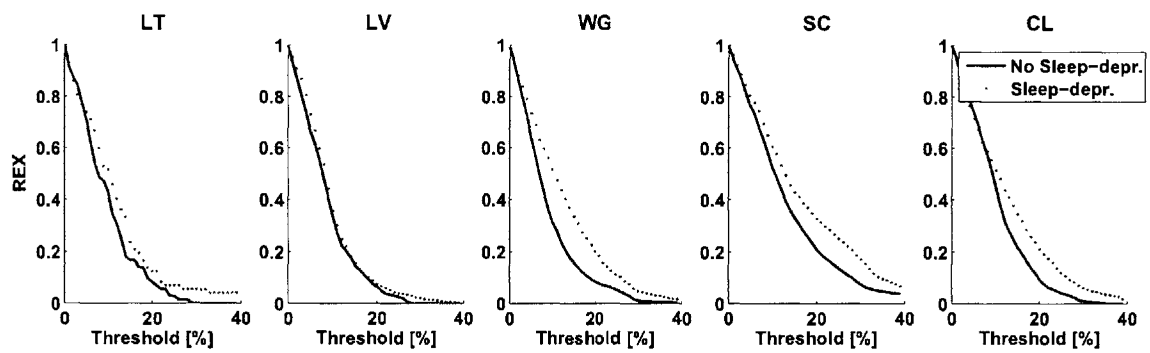

Figure 6-2: REX sampled over 350m

We examine five different tasks during lane tracking sessions: 1) Straight Lane Tracking (LT); 2) Straight Lane Tracking given a Lead Vehicle (LV); 3) Straight Lane Tracking given Wind Gusts (WG); 4) Straight Lane Tracking given Change of Steering Dynamics (SC); and 5) Curved Lane Tracking (CL). Detailed scenario settings have been described in Chapter 5. RMS error is generally used for a metric for tracking error measures.

Fig. 6-1 and Fig. 6-2 show average performance data of 12 subjects sampled over a distance of 350m which corresponds approximately to 13-15 seconds of the LT, LV, WG, SC and CL tasks. X-axis represents a threshold from the centerline of the road, which is given in percentage unit with 100% as the road width. For example, 30% threshold means $\pm 30\%$ from the centerline of the road. (50% threshold covers the whole road width.) Y-axis represents RMT in Fig. 6-1 and REX in Fig. 6-2. (Refer to Section 5.2.4 for definitions of RMT and REX.) Solid lines indicate data from the

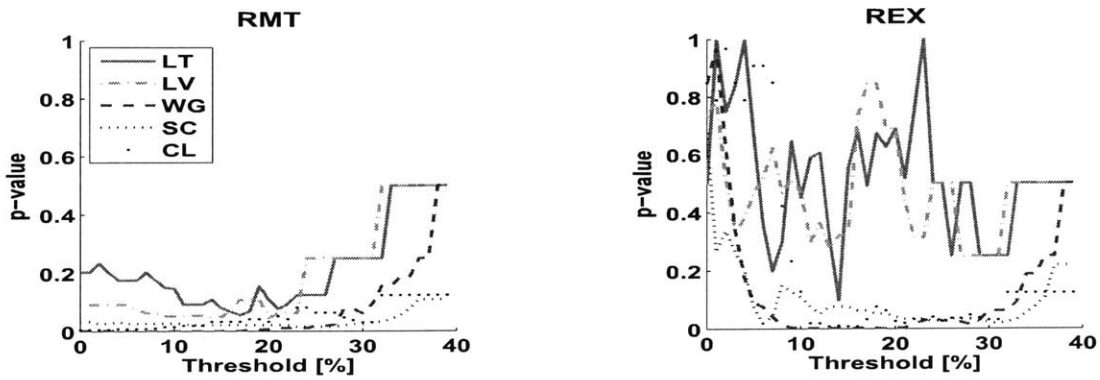

Figure 6-3: p-value calculated from Fig. 6-1 and Fig. 6-2

non-sleep-deprived group, and dotted line from the partially sleep-deprived group.

Both figures show that the dotted lines are above the solid lines for each lane tracking task, which implies that the performance of the partially sleep-deprived group could be worse than that of the non-seep-deprived group for all tasks. (A proper analysis will follow to see if there exist statistically significant differences between two groups.) Clearly, both RMT and REX are functions of the threshold; as it increases, the values of RMT and REX decrease. This is reasonable since the wider the threshold is, the easier the driver stays within the threshold, and the smaller the lane tracking error becomes. Moreover, both RMT and REX vs. threshold are 'L' shaped; RMT and REX vary rapidly around 0 to 10% of the threshold, and their rate of change decreases as the threshold increases. This implies that the lane tracking performance is sensitive to small threshold values. This trend is compatible with drivers' *safisficing* strategy for lane tracking.

Fig. 6-1 and Fig. 6-2 show possibilities of performance degradation in partially sleep-deprived drivers. Nonparametric statistical tests firmly claim that what we have seen in the previous figures are indeed non-trivial. Fig. 6-3 shows p-values calculated from data in Fig. 6-1 and Fig. 6-2. X-axis represents the same threshold as in the previous figures. Y-axis represents p-values. The left and right figure correspond to RMT and REX, respectively. p-values of LT, LV, WG, SC, and CL are plotted in lines of different styles and colors. We set $\alpha = 0.1$, and p-values less than α are considered to be significant.

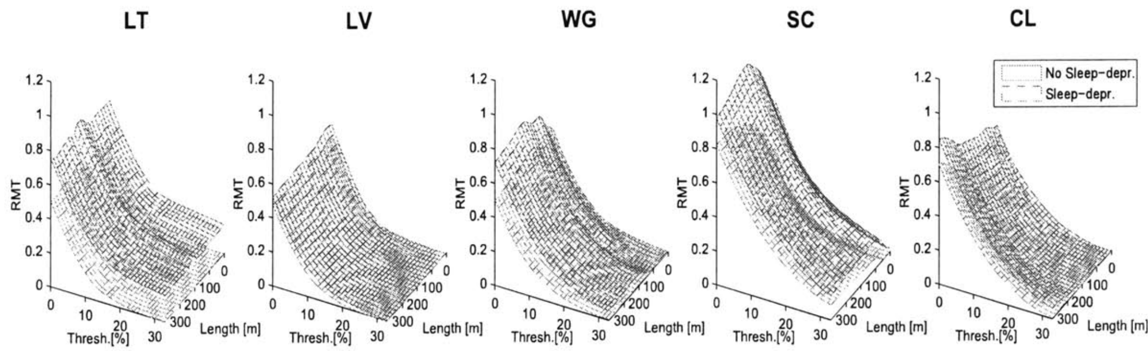

Figure 6-4: Threshold vs. Sampling length vs. RMT

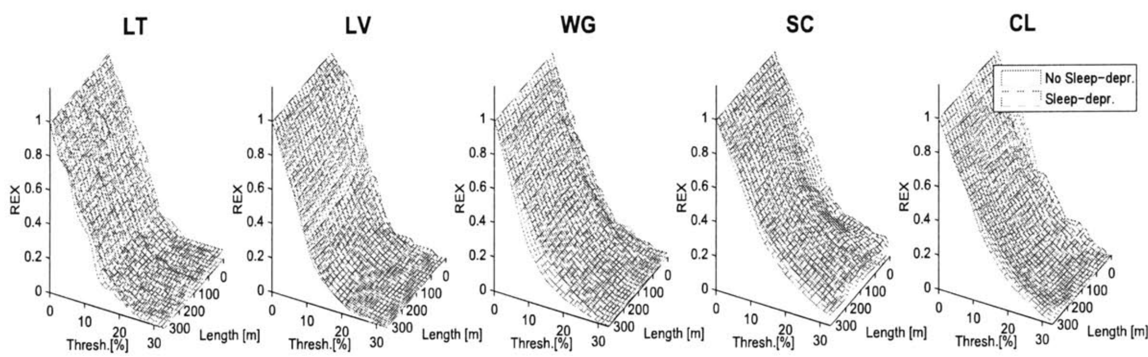

Figure 6-5: Threshold vs. Sampling length vs. REX

p-values in the left figure (RMT) are generally smaller than those in the right figure (REX). However, we can read the same trends from both RMT and REX figures; Whereas p-values of WG, SC, and CL are smaller than α for a good amount of thresholds, those of LT and LV are *not*. This result implies that partially sleep-deprived drivers perform worse than non-sleep-deprived groups in WG, SC, and CL, although they perform as good as in LT and LV in our data.

We also need to consider: how soon we can detect the performance differences between two groups and how they propagate as time evolves. We can extend Fig. 6-1 and Fig. 6-2 by introducing a sample length (how much data we need to collect) which are shown in Fig. 6-4 and Fig. 6-5. X-axis represents the same threshold as in Fig. 6-1 and Fig. 6-2. Y-axis is the sampling length in meters (5m-400m), which

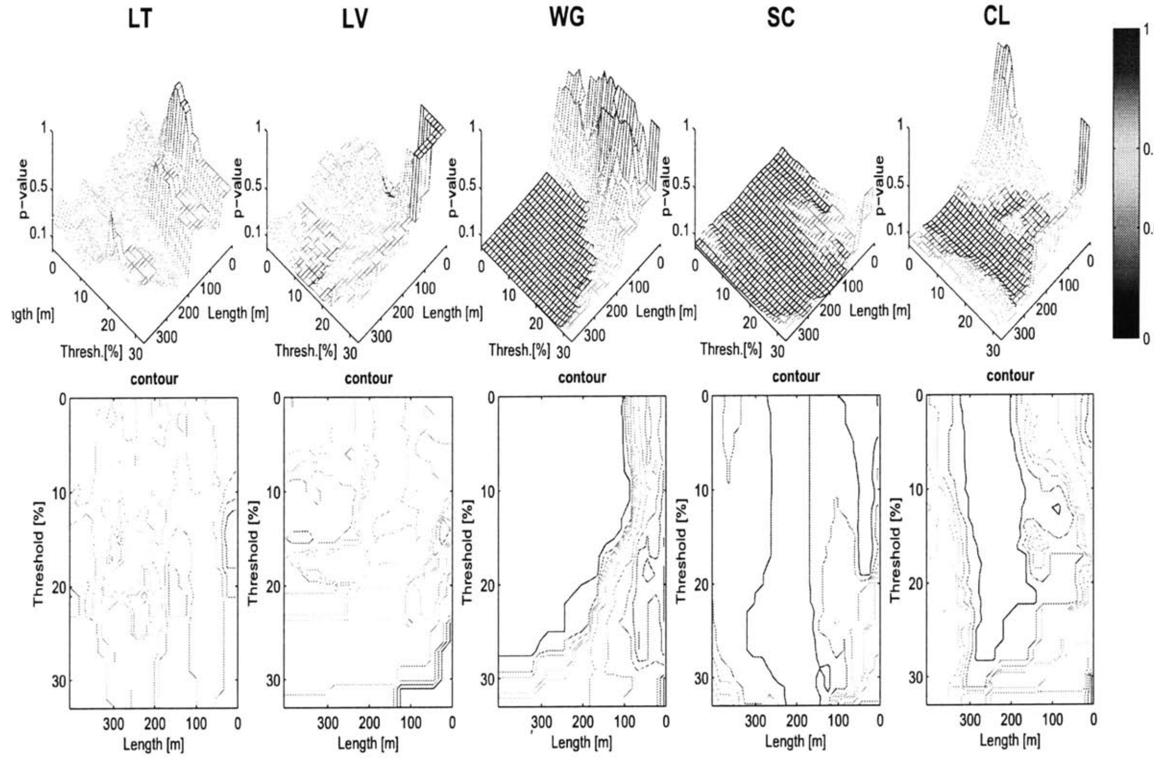

Figure 6-6: p-value of Fig. 6-4

shows how much data we need to detect the differences, if any. Z-axis represents RMT in Fig. 6-4 and REX in Fig. 6-5. Surfaces with solid/dotted lines indicate data from the non/partially sleep-deprived groups.

Fig. 6-4 and Fig. 6-5 visually confirm the same trends as those in Fig. 6-1 and Fig. 6-2. Now we have RMT and REX surfaces instead of lines. Clearly, both RMT and REX are functions of the threshold: as it increases, the values of RMT and REX decrease. It is not so clear in these figures that both RMT and REX are affected by the sampling length as much as by the threshold. Thus, the RMT and REX surfaces are again 'L' shaped surfaces with some folds between edges. It is difficult to see the effect of sampling length in these figures. Statistical tests may provide some information on the effect of sampling length as well as of the threshold.

Fig. 6-6 and Fig. 6-7 present the p-values calculated from RMT and REX measures respectively for the threshold (0-35%) and for the sampling length (5m-400m). Lower plots in Fig. 6-6 and Fig. 6-7 are the contours of the upper plots. Fig. 6-3 is one of

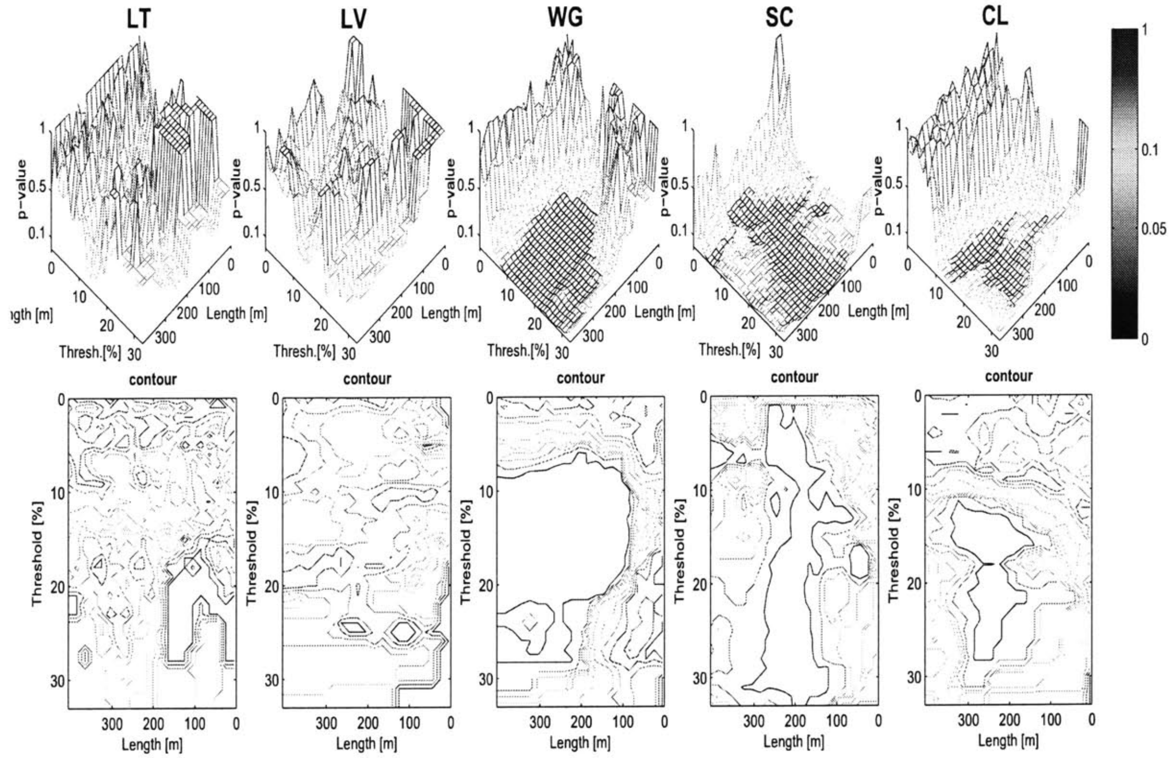

Figure 6-7: p-value of Fig. 6-5

the vertical cross sections of Fig. 6-6 and Fig. 6-7. p-values are plotted with the color map shown in the right-upper side of the figures; the color map has high resolution from p= 0 to p= $0.5\alpha = 0.05$, medium resolution from $p = 0.05$ to $p = \alpha = 0.1$, and low resolution from $p = 0.1$ to $p = 1$. This is because p-values greater than the threshold α are not as critical as p-values smaller than α. For example, if p-value is either 0.3 or 0.6, we mainly focus on the fact that the p-value is *greater than* α, not on the p-value itself. However, if the p-value is either 0.09 or 0.03, we may be interested in how close the p-value is to the threshold rather than the fact that the p-value is smaller than α.

The following interpretations apply to both Fig. 6-6 and Fig. 6-7, although Fig. 6-6 shows smaller p-values than Fig. 6-7. This is because RMT captures more detailed performances than REX. For LT and LV, p-values for most threshold and sampling length values are bigger than α. The curve is noise-like shape, which implies that it is difficult to differentiate the performance between non and partially sleep-deprived groups.

For WG, SC, and CL, p-values for extensive threshold and sampling length values are smaller than α, which asserts that the performance differences between non and partially sleep-deprived groups are significant in WG, SC, and CL. For WG, the effect of the sampling length is recognizable: as it increases, its p-value decreases. This may indicate that non-sleep-deprived group adapt themselves to disturbances faster than partially sleep-deprived group. For CS, the p-value is approximately 0 for most sampling lengths and thresholds, which suggests that the CS task should demonstrate distinct and significant performance differences between non and partially sleep-deprived groups. For CL, the differences are present, but the effective intervals are not as wide as for WG or CS.

We can observe that once drivers encounter abrupt changes caused by environment (WG), vehicle (SC), or challenging road geometry (CL), their adaptability to adapt to these changes differs, depending their sleep levels. However, if there is no excitation or disturbances introduced (LT or LV), drivers' performance shows little difference between different sleep levels. This implies that drowsy drivers may drive as well as alert drivers for common driving tasks without any disturbances. More in-depth explanation in conjunction with other performances are given in Section 6.1.7.

6.1.2 Steering Control Performance

Steering control is directly related to drivers' lane tracking performance. We have studied in Chapter 4 that the lateral position of the vehicle can be approximately expressed as a double integrator of steering movement of drivers. Thus, we can expect that the performance analysis of steering may provide a similar result with even either more sensitive or robust to sleep-deprivation levels of drivers than lane tracking performance.

Fig. 6-8 represents p-values of steering control between non and partially sleep-deprived drivers. All figure axes and legends are identical with those in Fig. 6-6. It shows more noisy surfaces than Fig. 6-6. We can find surface areas with small p-values in LV, WG, SC, and CL, though the trend is not so obvious as that of lane

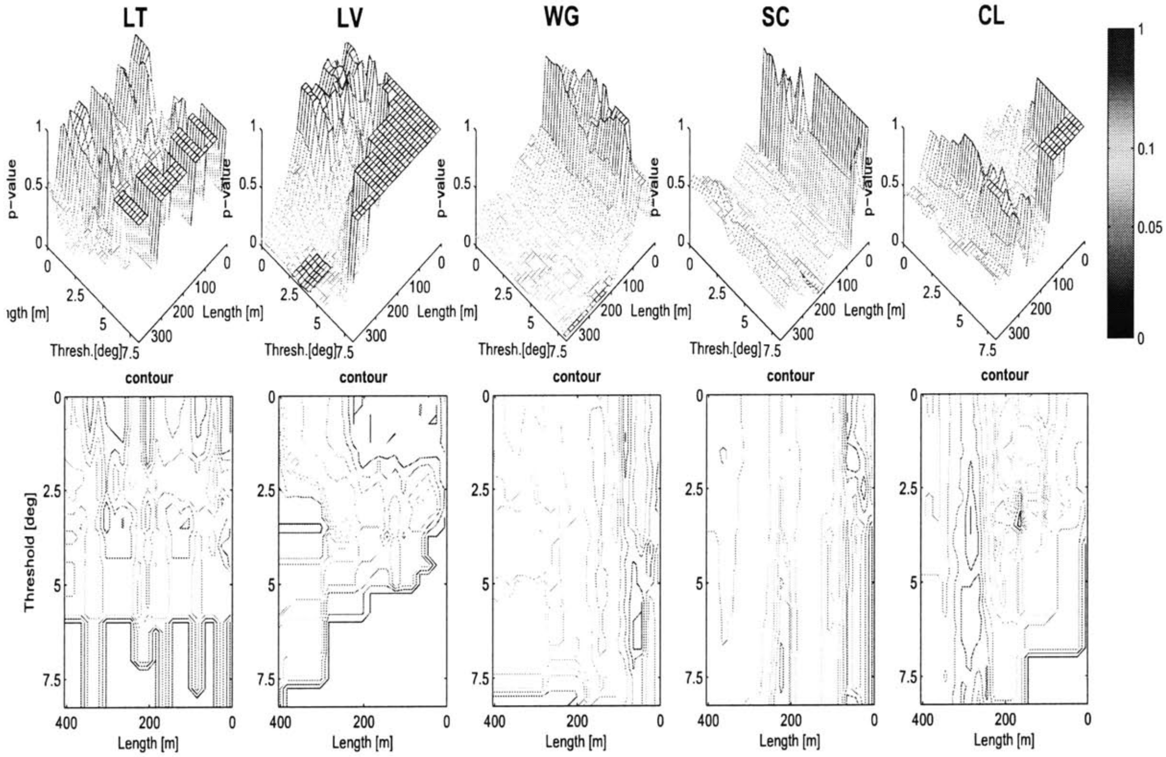

Figure 6-8: p-value of steering control

tracking performance. In Section 6.1.1, experimental data of lane tracking performance demonstrate clear differences in WG, SC, and CL. Steering control differences between non and partially sleep-deprived groups are not as much apparent, which suggests that drivers' control strategies (patterns, characteristics) not be affected by sleep deprivation.

6.1.3 Longitudinal Velocity and Throttle/Brake Performance

We are not able to find significant differences in longitudinal velocities in LT, LV, WG, SC, and CL. Throttle and brake control show the same trend.

6.1.4 Stimulus-Response Time Tasks

While driving on the road, we look in all directions monitoring traffic, road conditions, pedestrians, etc. At the same time, we listen to engine noise, radio, or ambulance sounds. Along with an ability to keep the vehicle on the roadway, it is critical for

Table 6.1: Mean, STD, and Spearman's coefficients of RT.

Mean value [sec]

	APVT	VPVT	SLCT	DLCT
No sleep-depr.	0.741	0.907	0.763	0.722
Sleep-depr.	0.927	1.078	0.814	0.857

STD [sec]

	APVT	VPVT	SLCT	DLCT
No sleep-depr.	0.248	0.251	0.099	0.099
Sleep-depr.	0.359	0.351	0.170	0.188

Spearman's correlation coefficients (ρ) between tasks.

	APVT	VPVT	SLCT	DLCT
APVT	·	·	·	·
VPVT	**0.9313**	·	·	·
SLCT	0.3200	0.1800	·	·
DLCT	**0.6270**	**0.6400**	**0.4574**	·

a driver to cope with unexpected or emergent situations for vehicle safety. We use various stimulus-response tasks to measure a driver's ability to react to external stimuli. These tasks are complementary to lane tracking tasks.

Specifically arranged for stimulus-response tasks are: 1) APVT (Auditory Psychomotor Vigilance Tasks); 2) DLCT (Double Lane Change Tasks); 3) SLCT (Single Lane Change Tasks); and 4) VPVT (Visual Psychomotor Vigilance Tasks). RT (Reaction Time), LR (Lapse Rate), and CRR (Correct Response Rate) are used as metrics for these stimulus-response tasks. Refer to Chapter 5 for detailed scenario settings and definitions of metrics.

Reaction Time

Table 6.1 shows the mean and standard deviation (STD) of RT for each sleep-deprivation level and task type, which is visualized in the boxplot, Fig. 6-9, as well. Each box has lines at the lower quartile, median, and upper quartile of the RT data. The whisker extends to the most extreme value within 150% of interquartile range. Outliers marked with + are data with values beyond the ends of the whiskers. A and B represent no sleep-deprivation and partial sleep-deprivation, respectively.

Fig. 6-9 shows that the RT of partially sleep-deprived group are slower than that of

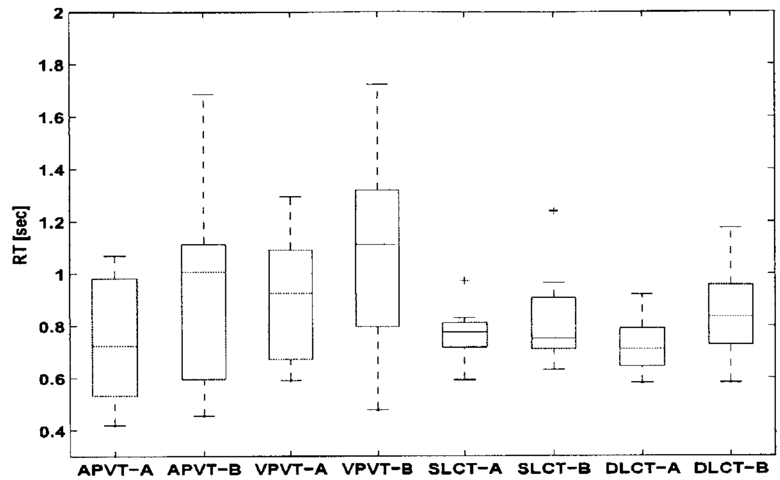

Figure 6-9: Boxplot of RT from stimulus-response tasks

non-sleep-deprived group in general. This observation is confirmed by such statistical tests as RT of APVT, VPVT, and DLCT, all of which show significant differences between partial and no sleep-deprivation groups, with p-values of 0.0034, 0.0269, and 0.0049, respectively. Previous research [34, 69] reported consistent results in Psychomotor Vigilance Tasks. However, SLCT does *not* show any significant difference between different sleep-deprivation levels.

We are also interested in correlations between tasks, since some tasks show performance deteriorations and others do not. A matrix containing the pairwise Spearman's rank correlation coefficient, ρ, is given in Table 6.1. Tasks with high ρ, i.e., tasks associated with p-values less than α, are marked with bold font. In Table 6.1, APVT, VPVT, and DLCT show high correlation with each other, whereas SLCT is only marginally correlated with DLCT and shows low correlation with APVT or VPVT. Thus, the tasks revealing significant performance differences between sleep-deprived and non-sleep-deprived groups (APVT, VPVT, and DLCT) are correlated with each other as well.

On the other hand, the RT can be also compared for these tasks. The RT of VPVT is significantly different from those of APVT, SLCT, and DLCT, with p-values of 0.0001, 0.0043, and 0.0015, respectively. A reaction to VPVT is slower than those to AVPT, SLCT, or DLCT. The difference between APVT and VPVT can be explained by the stimulus modality. It is known that drivers react faster to auditory stimuli than to visual cues [141], which is consistent with our data. The difference between VPVT and SLCT/DLCT can be explained by the driver's corresponding action for each task. In the response to VPVT, drivers need to make an additional hand/arm movement by pressing a button on the steering wheel. In contrast, drivers only need to rotate their arms to turn the steering wheel to perform lane changes in SLCT/DLCT.

An interesting result is that the performance of SLCT does not degrade even when the subjects are under partial sleep-deprivation. However, the performance of DLCT does. Note that the stimulus and task protocol of DLCT are identical with those of SLCT, while required amplitude of lane changes in DLCT is twice the lane change in SLCT. Such a lane change (required in DLCT) is not common in a real driving situation. Since SLCT is one of the routine driving tasks in the real world, our result suggests that drowsy drivers be able to maintain their normal level of performance if no external stimuli or unusual situations (such as DLCT) occur.

Lapse Rate

A lapse is a metric to measure a driver's inadequate performance when he/she does not respond to a stimulus in a timely manner. Thus, LR particularly provides information on retarded action, although it is calculated from RT. LR can be obtained from the definition in Eq. 5.7. The results are shown in Table 6.2 where the lapse threshold is set at 900 ms. The corresponding p-values for APVT, VPVT, SLCT, and DLCT are 0.0137, 0.0195, 0.1641, and 0.0156, respectively, which agrees with those of RT data: APVT, VPVT, and DLCT show a significant difference between partial and no sleep-deprivation groups, whereas SLCT does not.

The lapse threshold (900ms) leading to non-trivial results is greater than the thresholds used in previous studies [34, 69]. The reason is that our PVTs are randomly mixed with other types of tasks so that the rate of stimulus presentation is far lower than the sustained PVTs used in [34, 69]. It has been shown [19] that a greater percentage of signals is detected and responded more quickly, as the rate of signal presentation increases. Thus, instead of comparing LR with a given threshold,

Table 6.2: Mean and STD of Lapse

Mean value [sec]

	APVT	VPVT	SLCT	DLCT
no sleep-depr.	0.3000	0.4000	0.1667	0.1333
Sleep-depr.	0.5167	0.5583	0.3000	0.2833

STD [sec]

	APVT	VPVT	SLCT	DLCT
no sleep-depr.	0.3275	0.3618	0.1875	0.1969
Sleep-depr.	0.4130	0.3605	0.2629	0.2167

we note the trend of LR difference, i.e., the trend of p-value, as the threshold varies. We desire to figure out whether LR is robust enough when the lapse threshold varies within a reasonable interval. If LR were not sensitive to the thresholds, the validity of LR as an indicator of sleep deprivation would be solidified.

Fig. 6-10 presents the p-values as the lapse threshold varies for APVT, VPVT, SLCT, and DLCT. It shows that APVT, VPVT, and DLCT have small p-values for substantial intervals of the threshold, e.g., p-values are less than α for VPVT whenever the threshold is greater than around 850 ms. This indicates that LR can be a good performance indicator for APVT, VPVT, and DLCT, since it is not sensitive to the lapse threshold. For SLCT, however, we can rarely see small p-values even though the curve is "U" - shaped. We may be able to see some significant differences in SLCT if we increase sample size or change other factors. However, as is demonstrated in Fig. 6-10, the degree of performance deterioration under sleep deprivation in SLCT is clearly less than that in APVT, VPVT, or DLCT. This result is consistent with the result from RT analysis.

The p-values shown in Fig. 6-10 have been calculated from all subjects. It is shown that the thresholds that yield small p-values are indeed optimal for each subject. Fig. 6-11 shows the LR of Subject 1,9, and 10 for various values of its thresholds. Clearly, LR decreases as its threshold increases. However, each subject has his/her own optimal lapse threshold: it would be around 0.7 sec for Subject 1, and around 1.0 sec for Subject 10. Subject 9 seems to have no acceptable threshold to differentiate non and partially sleep-deprived groups. We will detail individual differences of

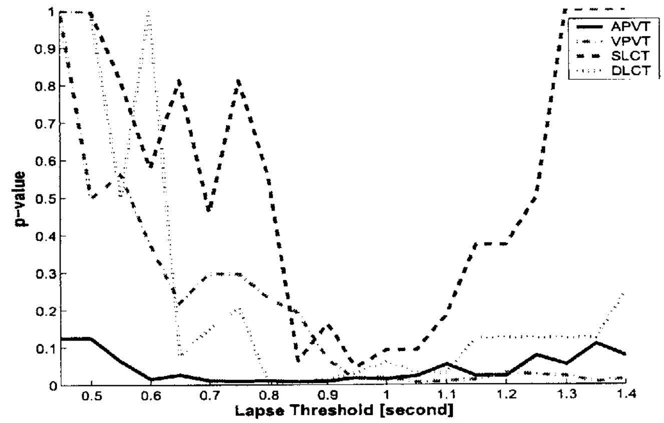

Figure 6-10: Lapse threshold vs. p-value

subjects in Chapter 7.

Correct Response Rate

Both RT and LR measure how fast drivers respond to given stimuli. At the same time we are interested in the validity of drivers' responses. For APVT and VPVT, drivers are supposed to press a green button on the steering wheel immediately after a given stimulus. The steering wheel has other buttons, and we can observe if drivers press incorrect buttons. The data show that APVT and VPVT have no significant differences in accuracy between non and partially sleep-deprived groups. For SLCT and DLCT, drivers are supposed to change lanes immediately once an overhead lane change sign appears. We can observe if drivers change lane inappropriately to wrong lanes. The data show that SLCT and DLCT have no significant differences in accuracy between non and partially sleep-deprived groups.

6.1.5 Application of the Crossover Model to Lane Change Tasks

In the previous sections, we consider SLCT and DLCT as stimulus-response tasks, and their performance metrics are the reaction times of the associated tasks. At the same time, lane change tasks can be considered as tracking tasks - tracking tasks with unit step input. We now employ McRuer's Crossover Model to analyze SLCT and DLCT in continuous tracking task category.

McRuer's Crossover Model [56, 66, 83, 84] claims that, for continuous tracking

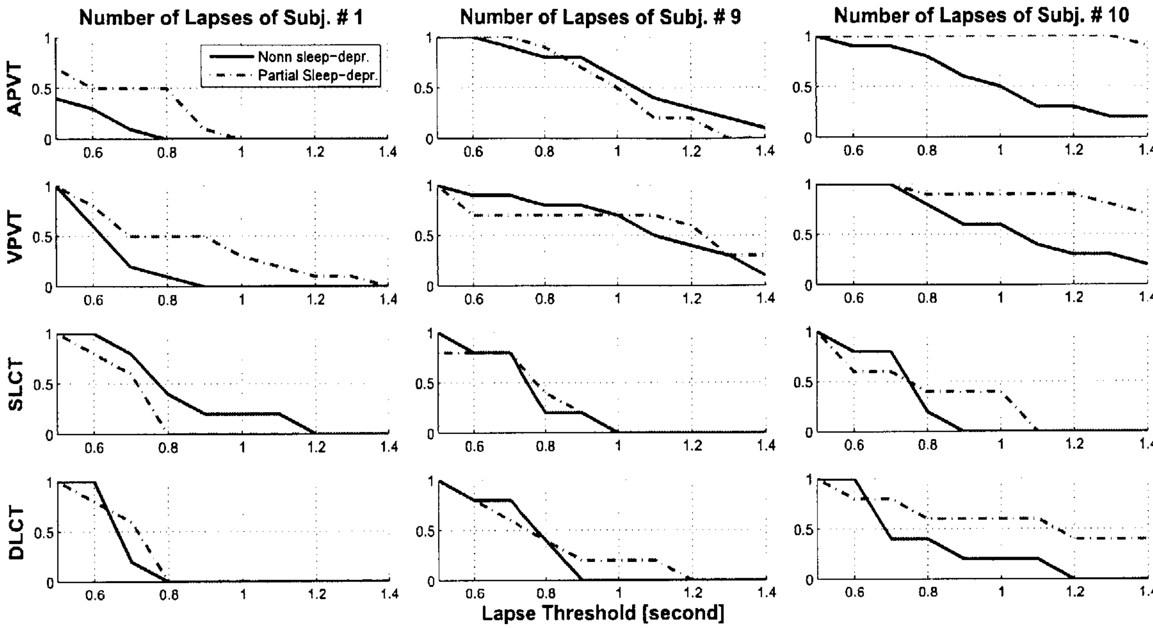

Figure 6-11: Lapse threshold vs. Lapse Rate for Subject #1,9, and 10

tasks, human adapts themselves to the system in such a way as to make the total open-loop transfer function behave as a first-order system with *gain* and *effective time delay*. Please, refer Section 5.2.4 for a description of the model. A detailed specification of the Crossover Model such as crossover frequencies can be found in [82, 83, 118]. In case of both SLCT and DLCT, human presented in Fig. 6-12 corresponds to a driver, plant to a vehicle, reference signal to the appearance of LCT sign, output signal to the lateral position of vehicle, and perceived error to the reference minus output signal. Fig. 6-13 represents a set of experimental data (DLCT) from a subject, which shows signal, output signal, and perceived error from DLCT.

Assuming that the open-loop transfer functions can be simplified as the Crossover Model, we can estimate its gain K and effective time delay τ for each subject for both SLCT and DLCT, which are summarized in Appendix B.1. With these estimated parameters, we can run statistical tests to determine if any significant differences exist between non and partially sleep-deprived groups.

Table 6.3 summarizes p-values. We are not able to see any significant differences in gain K for both SLCT and DLCT. However, only in DLCT, we can observe an appar-

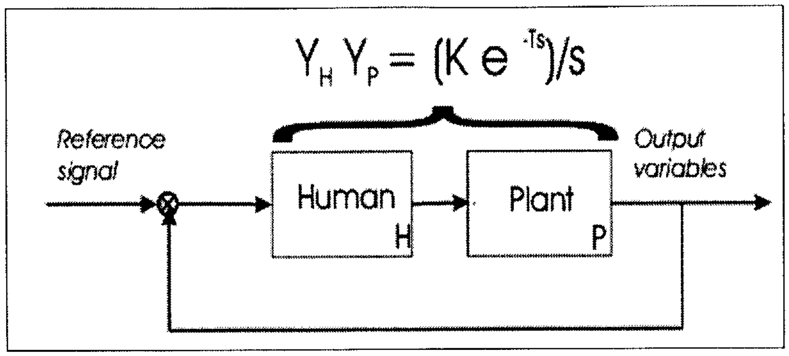

Figure 6-12: Block diagram of the Crossover Model

ent difference in effective time delay τ. This is compatible with the stimulus-response tasks if we consider the effective time delay of continuous tasks to be equivalent to the reaction time of stimulus-response tasks.

6.1.6 Order Effects of Experiments

Since the above results are obtained from with-in subject data, we have a pair of data from each subject, i.e. one from non-sleep-deprived condition and the other from partially sleep-deprived condition. As is described in Chapter 5, the order of experiment sessions are counter-balanced; half of the randomly selected subjects completed a session under no sleep-deprivation prior to a session under partial sleep-deprivation, and the other half completed both sessions in a reverse order. However, it still remains to examine if there exist any order or learning effects in the experimental data from the repetitive experiments for each subject.

Learning effects of all the metrics introduced in the previous sections have been examined. For lane tracking performances such as RMT and REX, we are not able to find any significant order effects. However, for steering control, we can observe some differences between the first and second experiment sets. Since we have not included WG and SC in our demo drive, it is reasonable to see some order effects. For CL, we let drivers exercise on a curvy road in demo drive, but not on the same curvature in the main experiment such that drivers may need to adjust their control strategy. The important thing is that the difference between the first and second experiment set are negligible, compared with that between different sleep-deprivation levels. This

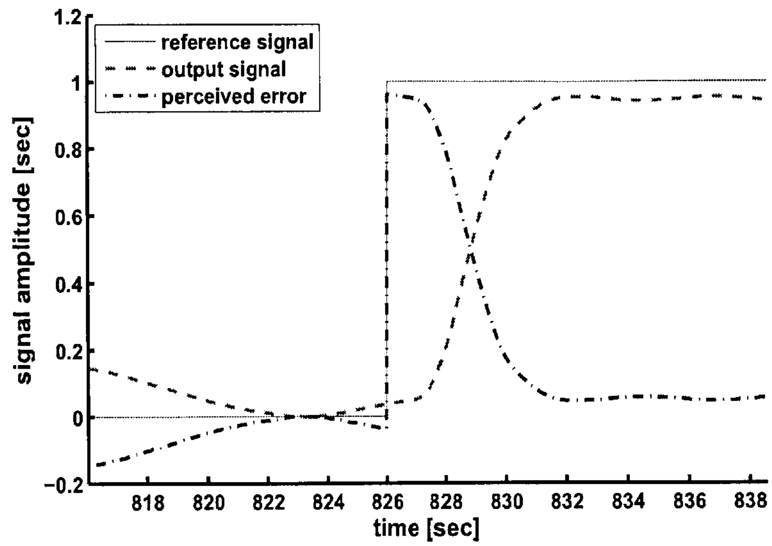

Figure 6-13: LCT data applied to the Crossover Model

justifies to accept the results from the previous sections.

Longitudinal velocity and brake control have also shown no order effects. For throttle control, there exist some significant differences between the first and second experiment set. This can be interpreted as steering difference in CL explained in the previous paragraph. For RT, LR, and CRR from stimulus-tasks, we have not been able to detect any significant differences. Thus, we can conclude that order effects are not negligible in our experiment.

6.1.7 Comprehensive Analysis

We can analyze the experimental results within the frame of information processing introduced by Rasmussen [117]. The Rasmussen classification claims that human behavior is based on a *skill, rule* and *knowledge* hierarchy. Skill-based tasks need the least cognitive resources; little or no conscious control is used to perform an action. These tasks include highly automated tasks such as walking. Rule-based tasks need more information processing stages to properly perform relevant tasks. They require us to identify the system state to execute the appropriate rules. Knowledge-based tasks are the highest level tasks involving advanced problem solving or decision making. Fig. 6-14 depicts the Rasmussen hierarchy.

Table 6.3: p-values for gain K and effective time delay τ between non and partially sleep-deprived groups

	SLCT	DLCT
gain K	0.5543	0.5095
effective time delay τ	0.1484	**0.0408**

Obvious examples of skill-based tasks from our simulated driving include LT and LV; they are common driving tasks for which drivers need no conscious control. However, other common driving tasks such as WG, CS, and CL hold both skill and rule-based task characteristics. Drivers need to pay more attention to control their vehicles since unexpected external disturbances may occur in these tasks. In our experiment, WG, CS, and CL are categorized as rule-based tasks, because they are not practiced throughly before the experiment.

Most stimulus-response tasks such as APVT, VPVT, and DLCT have rule-based task characteristics; a set of rules are assigned to each task, and drivers are supposed to follow them. However, SLCT also possesses skill-based characteristics, because drivers perform SLCT very often and are familiar with them. Thus, we classify SLCT as a skill-based task, whereas APVT, VPVT, and DLCT as rule-based tasks.

We have not included any knowledge-based tasks in our experiment, but an example could be path planning. On the right side of Fig. 6-14, some simulated tasks from the experiment are listed for each hierarchy level.

In our experimental data, recall that the sleep-deprived drivers performed worse only in tasks 1) WG, SC, CL (tracking tasks with disturbances) and 2) APVT, VPVT, DLT (stimulus-response tasks). We were not able to find performance differences in LT, LV, and SLCT between two different sleep-levels. When connecting these observations with the classification introduced in Fig. 6-14, we find that the performance of partially sleep-deprived drivers *degrades mainly in rule-based tasks* rather than in skill-based tasks. This result implies that drowsiness has a greater effect on tasks related to the rule-based (medium-level) cognitive functions than skill-based (low-level) cognitive functions. Considering that most common driving tasks are skill-based tasks, this interpretation uncovers important characteristics of drowsy driving.

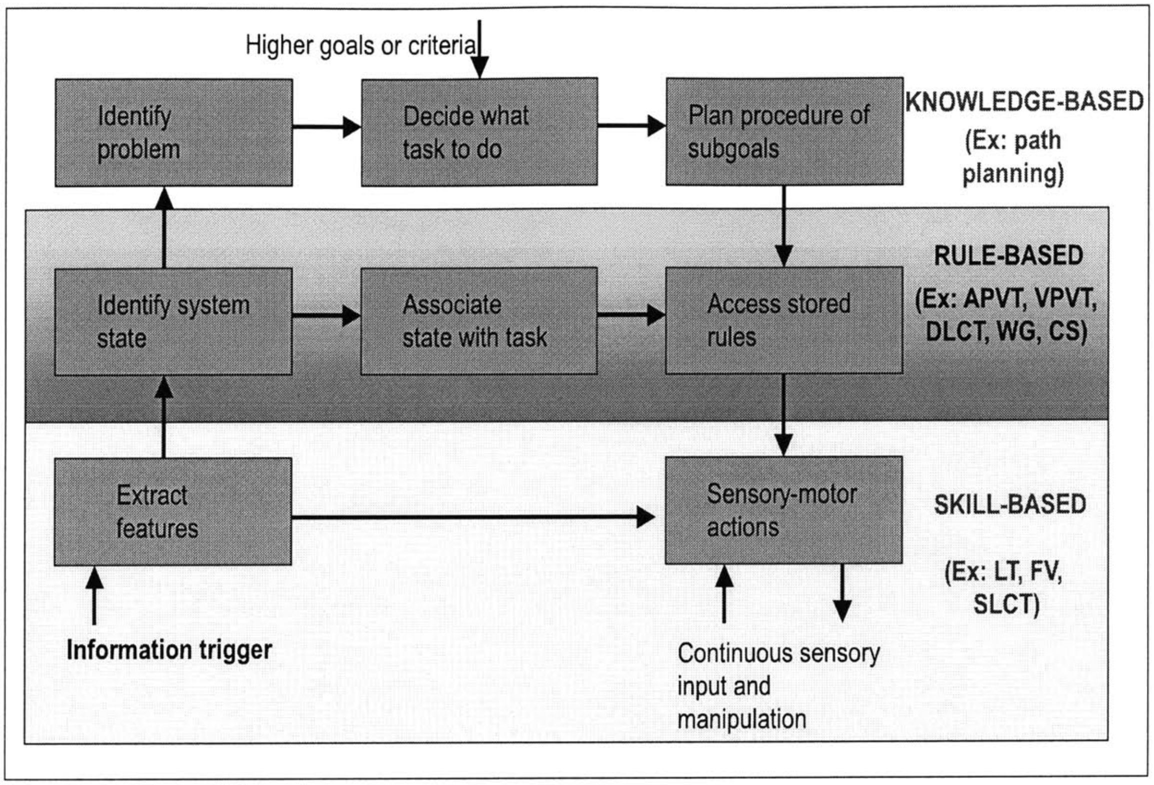

Figure 6-14: The Rasmussen skill-, rule-, knowledge-based classification with simulated task examples [117]

Drowsy drivers are robust enough to continue such routine tasks as lane tracking or single lane change tasks. However, their performance for medium-level, rule-based tasks deteriorates. Drowsy drivers may continue common driving tasks when there is no disturbances. The robustness of drowsy drivers in skill-based tasks confirms that drowsy driving is unobservable in some aspects and suggest that those tasks should not be used as drowsy driving indices.

However, this argument must be solidified by further experiments performed in a motion-based simulator or a real-driving situation. It has been noted [44] that drivers' lane tracking performance is better in motion-based simulators than in fixed-based simulators. We have also observed in Chapter 4 that the vestibular inputs to drivers are one of the critical cues for driving. Thus, further studies are needed to address this issue to cement our claims.

We have studied rule and skill-based tasks, but not knowledge-based tasks. Higher-level functions such as knowledge-based tasks should be addressed in further studies.

Complex tasks are often thought to be more sensitive to sleep loss than simple tasks, yet the tasks that most often show sleep loss effects early and profoundly are simple sustained attention RT tasks, which can be hardly considered to be complex [32]. Simple reaction time and auditory vigilance tests, which are considered as medium-level tasks in our experiment, are the most sensitive to sleep, and thus the most commonly used in sleep loss research. These tests are simple, dull, monotonous, easy to score, and not prone to large practice effects [32]. As these are so mundane, the degree to which they primarily assess cerebral functioning is debatable.

If the cerebral cortex is the major beneficiary of sleep, then the detrimental effects of total sleep loss would be more obvious (initially) with those tests of cerebral function that are exacting rather than with simpler tasks such as reaction time. However, this is not the case, as there is a confounding effect of an additional performance degradation due to tedium and a loss of interest in the task [32]. Human motivation could be a main factor for deciding the performance in high-level tasks, and further studies may be required to address this issue.

6.2 Power Analysis

In the previous sections, we have drawn a conclusion based on nonparametric statistical tests. While some results have shown significant differences, such critical parameters leading to those results as sample sizes, significant criterion α, etc., have not been investigated for experimental settings. The main goal of the power analysis is to determine how many samples are necessary for accurate and reliable statistical judgment, or how likely the statistical test detects the effect of a given sample size in a particular situation [25]. Too small sample sizes would not provide reliable results, whereas too large sample sizes would waste time and resources. Here we briefly introduce fundamentals on power analysis and statistical methods. Refer to [25] for more details.

Power measures the sensitivity of a significant test to detect a real difference if any. It is the likelihood of achieving the statistical significance. We list its relevant terminologies below:

Table 6.4: Decision vs. actual condition [70, 144]

		State of the World	
		H_0	H_1
Decision	H_0	Correct Acceptance	Type II Error (β)
	H_1	Type I Error (α)	Correct Rejection

- *Effect size* is the degree to which a phenomenon under study is present on the population.
- H_0 is a null hypothesis.
- H_1 is an alternative hypothesis.
- *Type I Error*, also known as an "error of the first kind", an α error, or a "false positive", is the error of rejecting a null hypothesis when it is actually true.
- *Type II Error*, also known as an "error of the second kind", a β error, or a "false negative", is the error of accepting a null hypothesis when the alternative hypothesis is a true state of nature [25].

Given these terms, power is given as 1-β. Table 6.4 tabulates the above quantities for actual condition and decision. Among numerous literatures on the Signal Detection Theory, Kuchar and Yang [70, 144] specifically deal with warning systems using System Operating Characteristics. The following factors influence the power.

- Sample size: In general, the larger the sample size, the larger the power . However, increase in sample size generally incurs increase in time, money and effort. Consequently, it is important to make sample size *large enough*, but to avoid redundancy.
- Effect size: Measure of the distance between H_0 and H_a. Standardized mean difference between two groups. For the t-test, effect size index $d = \frac{m_a - m_b}{\sigma}$ refers to the underlying population rather than a specific sample where m_a = mean of group a, m_b = mean of group b, and σ = standard deviation. In the case the null hypothesis is wrong by a substantial amount, the power will be also high.

Table 6.5: Effect size and power for sample size and data

	Effect size	Power
LT	0.479	0.451
LV	0.185	0.202
WG	1.78	0.999
SC	1.19	0.946
CL	1.49	0.99

- Significant criterion α: Trade-off between Type I-error α and Type II error β.
- The level of error in experimental measurements: Measurement error acts like 'noise' that can bury the 'real' signal of experiments.
- Statistical test: Some statistical tests are inherently more powerful than others.

Discovering that the difference between two sample means is *not* statistically significant, we *cannot* reject the null hypothesis. Does this imply that there is *no* difference or that the null hypothesis is true? It does *not* mean that the population effect Size is literally zero, but rather that it is negligible.

In case of our data, we have $\alpha = 0.1$, $\beta = 0.2$, desired power $= 1 - \beta = 0.8$, and sample size $N = 12$. Then, from the formula from [25], the detectable effect size turns out to be 0.8773.

Nonparametric tests (and paired t-tests) of WG, SC, and CL show significant performance differences, which means that the effect size of WG, SC and CL is greater than the 'detectable' effect size. Nonparametric tests (and paired t-tests) of LT and LV displays negligible performance differences, which means that the effect sizes of LT and LV are *not detectable*, given our sample size N, α, desired power, etc.

More samples could lead to a different results. However, we can observe that the effect sizes of WG, SC, and CL differ from that of LT and LV; the degree of performance deterioration is larger in WG, SC, and CL than in LT and FV.

Table 6.5 summarizes the effect sizes and powers for LT, LV, WG, SC, and CL, which are calculated from REX with threshold = 15% and sampling length = 200m. We can observe clear differences in the effect size and its associated power value between LT, LV and WG, SC, CL.

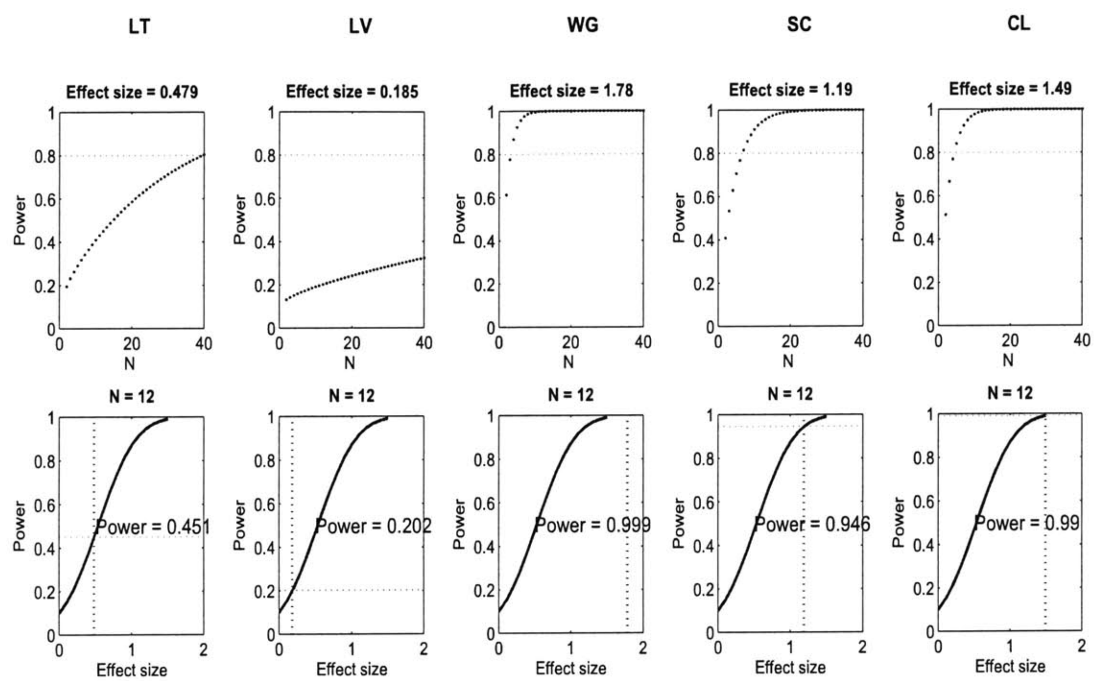

Figure 6-15: Graphical representation of effect size and power

Fig. 6-15 is a graphical representation of the power analysis. Each column represents each task, i.e., LT, LV, WG, SC, and CL. Upper plots depict estimated power vs. sample size varying from 1 to 40. X-axis corresponds to the sample size, Y-axis to Power. Since our required power is 0.8, we can read the required sample size N based on the effect size calculated from the experimental data. Lower plots show estimated power vs. effect size varying from 0 to 2 for $N = 12$. For each effect size calculated from the experimental data, we can read the corresponding power for each task. (They are summarized in Table 6.5.)

Fig. 6-16 shows a graphical representation of Type I and Type II error for each task. Our significant criterion α is set to be 0.1 and the area of the shaded region of upper plots is 0.1. When we extend this threshold to H_1(Partially sleep-deprived groups) , we can visualize the Type II error, which is shown in the dark shaded area in lower plots. It is seen that the Type II errors for LT and LV are larger than those of WG, SC, and CL.

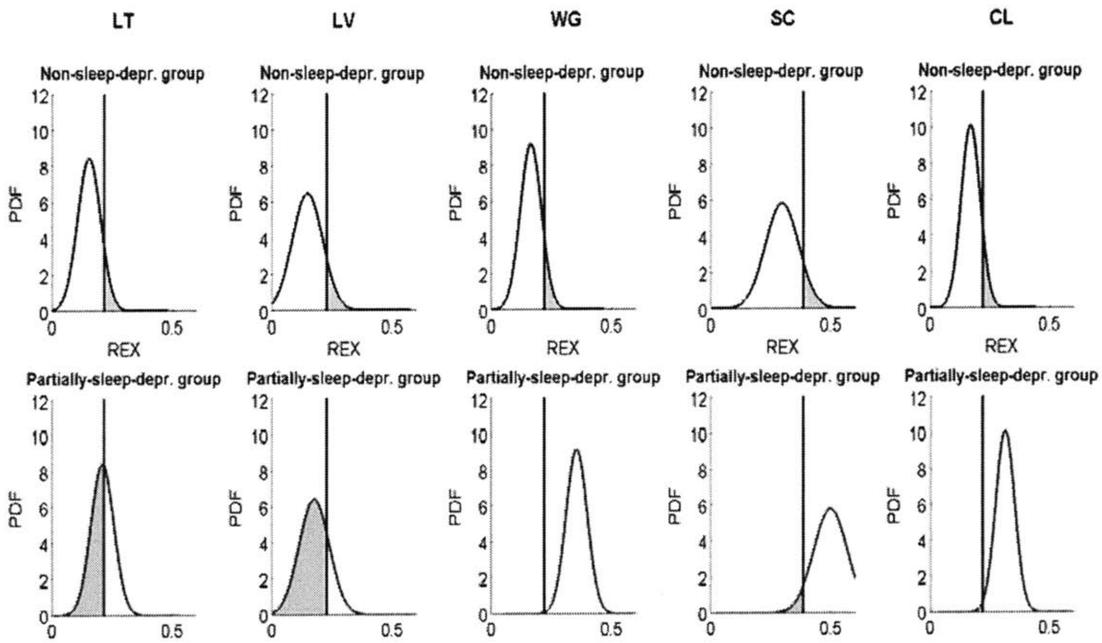

Figure 6-16: Graphical representation of Type I and II errors

6.3 Summary

Table 6.6 summarizes the statistical disclosure from the previous section. We have performed extensive analysis on driver-vehicle data from the experiment presented in Chapter 5. First, we have analyzed with-in subject performance differences between two different sleep-deprivation levels for various driving tasks. Non-parametric statistical tests have revealed significant differences between two groups. In terms of lateral lane tracking errors, we have been able to see the performance degradation clearly in partially-sleep-deprived groups for wind gust condition, change in steering dynamics, and curvy roads. However, our data have shown negligible performance differences in lane tracking errors with no disturbances on straight road and with a lead vehicle. Most stimulus-response tasks have shown the significant performance degradation as well: Auditory Psychomotor Vigilance Tasks, Visual Psychomotor Vigilance Tasks, and Double Lane Changes Tasks. Our data analysis have shown that a driver's performance degrade little in Single Lane Change Tasks. These observations have led to a conclusion that under sleep-deprivation, performance in rule-based tasks deteriorate to a greater extent than that in skill-based tasks. Corresponding analysis on order effects and power analysis have been discussed as well. We have applied the Crossover Model to both Single and Double Lane Change Tasks to understand them as continuous tracking tasks rather than discrete stimulus-response tasks, which have also provided consistent outcomes. Overall, we have identified the characteristics of drowsy driving.

Table 6.6: Summary of experimental data analysis

Performance	Task	Significant findings
lane tracking (RMT, REX)	LT	x
	LV	x
	WG	o
	SC	o
	CL	o
steering	LT	x
	LV	x
	WG	v
	SC	v
	CL	v
longitudinal velocity	LT	x
	LV	x
	WG	x
	SC	x
	CL	x
throttle	LT	x
	LV	x
	WG	x
	SC	x
	CL	x (order)
stimulus-response rapidity (RT, LR)	APVT	o
	VPVT	o
	SLCT	x
	DLCT	o
stimulus-response accuracy (CRR)	APVT	x
	VPVT	x
	SLCT	x
	DLCT	x
τ	SLCT	x
	DLCT	o
K	SLCT	x
	DLCT	x

Chapter 7

Design of Drowsy Driver Detection Systems

Up to this point, we have focused on finding performance differences between drivers who have different levels of sleep deprivation. A variety of driving or secondary tasks are examined for the purpose. In this Chapter, our focus is on inferring drivers' states based on their performances. This will be made possible by modeling our experiments in a probabilistic graphical model, the Bayesian network (BN). We devise a systematic way to detect human drowsiness, and a structure of the framework is built. Utilizing experimental data obtained from Chapter 5, we also provide quantitative guidelines applying both Static and Dynamic Bayesian Networks. Finally, this Chapter concludes with guidelines for the design of drowsy driver detection systems.

7.1 Introduction to Bayesian Networks

Numerous challenges are present in fatigue modeling and monitoring. First, fatigue is not directly observable and can only be inferred from the available observations. (In Chapter 2 we have investigated drowsy driving detection techniques in three different categories: by physiological signals, by physical changes of drivers, and by driver-vehicle data.) Second, the sensory observations are often ambiguous, incomplete, uncertain, and dynamically evolving over time [54]. Thus, a systematic method handling this uncertainty is necessary. Third, another difficulty lies in the quantification of psychological and behavioral changes [114]. Drowsiness or fatigue are often subjective (drivers' feeling and driver alertness states are not always same), and their symptoms are qualitative. We need to develop a standardized metric to effectively process observation data.

A myriad of methods have been presented for fusing information from disparate sources. These methods include probabilistic methods (e.g., Bayes theorem), evidential reasoning (e.g., Dempster-Shafer theory), Kalman filter, fuzzy theories, and neural networks, with a majority of methods based on fuzzy theories [54]. Among the various methods, we utilize the Bayesian network (BN) paradigm because it is capable of incorporating prior information and of explicitly modeling uncertainties and temporal aspects of the problem, as well as modeling data at different levels of abstraction.

A BN is a state-of-the-art knowledge representation scheme dealing with probabilistic knowledge. Also referred to as graphical model, a BN is a graphical representation of the joint probability of a set of random variables, with the conditional independence assumption explicitly embedded in the network [54]. A BN is capable of modeling dependencies and uncertainties between variables [112], and recently has been introduced in drowsiness detection techniques based on monitoring the physical behavior or drivers. It has been shown that the BN is able to capture dynamics associated with fatigue, and a corresponding BN is developed when physical indicators such as eye gaze are being monitored [54].

Graphical models combine probability theory and graph theory. They provide a tool for dealing with two challenging problems: uncertainty and complexity [57]. Probabilistic graphical models are graphs in which nodes represent random variables, and the (lack of) arcs represent conditional independence assumptions. Hence, they provide a compact representation of joint probability distributions. The conditional independencies mean that we can store and compute the joint probability distribution more efficiently. For example, if we have N binary random variables, an atomic representation of the joint, $P(X_1, \cdots, X_N)$ needs $O(2^N)$ parameters, whereas a graphical

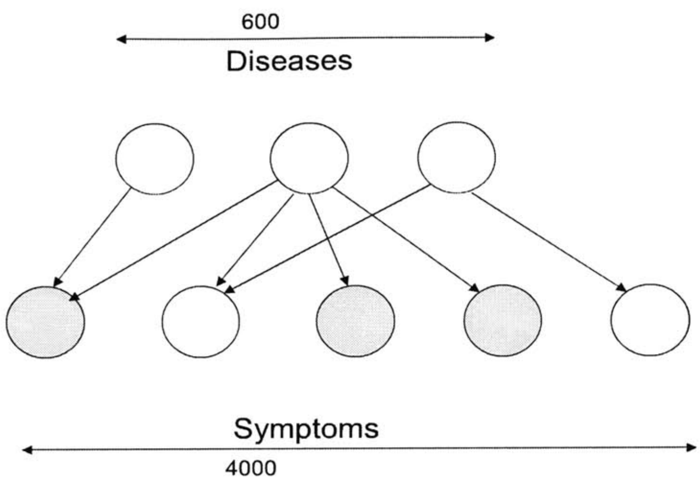

Figure 7-1: QMR-DT model [90]

model may need exponentially fewer, depending on which conditional assumptions we make [91, 112].

There are two main kinds of graphical models: undirected and directed. Undirected graphical models, also known as Markov networks or Markov random fields (MRFs), are more popular in the physics and vision communities. Directed graphical models, also known as Bayesian networks (BNs), belief networks, generative models, causal models, etc., are more popular with the AI and machine learning communities. It is also possible to have a model with both directed and undirected arcs, which is called a chain graph [90, 91].

The most widely used BNs are undoubtedly the ones embedded in Microsoft's products, including Answer Wizard of Office 95, the Office Assistant of Office 97, and over 30 Technical Support Troubleshooters [90]. BNs originally arose out of an attempt to add probabilities to expert systems, and this is still the most common use for BNs. A famous example is QMR-DT, a decision-theoretic reformulation of the Quick Medical Reference (QMR) model [90].

In Figure 7-1, the top layer represents hidden disease nodes, and the bottom layer represents observed symptom nodes. The goal is to infer the posterior probability of each disease given all the symptoms, which can be present, absent, or unknown.

Another interesting fielded application is the Vista system [51]. The Vista system is a decision-theoretic system that has been used at NASA Mission Control Center in Houston for several years. The system uses Bayesian networks to interpret live telemetry and provides advice on the likelihood of alternative failures of the space shuttle's propulsion systems. It provides tools for real-time control and quantifies information for the user [51]

7.2 Static Bayesian Networks

We first utilize Static Bayesian networks (SBN) to infer driver drowsiness based on our experimental data. A Bayesian network is a directed acyclic graph in which each *node* is annotated with quantitative probability information. The full specification is given as follows [53, 90, 112].

- A Bayesian network consists of a set of *variables* and a set of *directed edges* between variables.
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed edges from a *directed acyclic graph* (DAG).
- For each variable A with parents $B_1, \cdots, B_n$, there is a corresponding potential table $P(A|B_1, \cdots, B_n)$

If two variables are d-separated, then changing the uncertainty on one does not change the uncertainty on the other [59]. (Appendix B.3 explains details of d-separation.) The following is a useful theorem to keep in mind [53].

Theorem: If A and B are d-separated given evidence e, the $P(A|e) = P(A|B, e)$.

In BNs, an arc from A to B can be informally interpreted as indicating that A *causes* B. (The intuitive meaning of an arrow in a properly constructed network is usually that X has a direct influence on Y.) Hence, directed cycles are disallowed. More in-depth discussion concerning the difference between causality and mere correlation can be found in [90, 59]. A general introduction to BNs can be found in [53, 90, 91, 112].

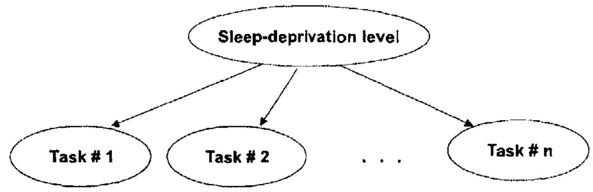

Figure 7-2: A bi-partite structure with only one parent node for each task performance

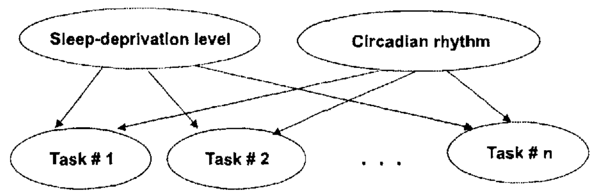

Figure 7-3: A bi-partite structure with two parent nodes for each task performance

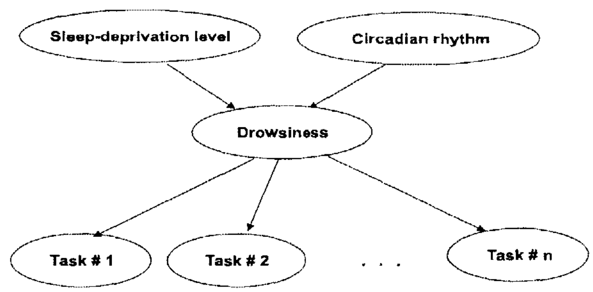

Figure 7-4: A multi-level structure with an introduction to Drowsiness node

7.2.1 Formulation of SBN

The topology of an SBN - the set of nodes and directed arcs- specifies the conditional independence relationships that hold in the domain. Once the topology of the BN is laid out, we only need to specify a conditional probability distribution for each variable, given its parents. The combination of the topology and the conditional distributions suffices to calculate the full joint distribution for all the variables.

Topology of the SBN

We first construct the structure of an SBN for drowsy driving detection problems. Fig. 7-2 to Fig. 7-4 show examples of possible SBN structures.

Fig. 7-2 shows a bi-partite structure with only one parent node for each task performance. This structure directly reflects our experimental setup described in

Chapter 5; we had one Independent variable, discrete sleep-deprivation level of drivers, and Dependent variables were task performances. What we have controlled, i.e. sleep-deprivation level, is modeled as a parent node in Fig. 7-2. Each task performance such as performance of APVT, CL, DLCT, EM, LT, LV, SC, SLCT, VPVT, and WG is a child-node of the sleep-deprivation level. They are shown as Task #1, #2, $\cdots$,#n in Fig. 7-2. We do not include any direct links between each task performance. Thus, each task performance is conditionally independent given its parent, sleep-deprivation level.

Fig. 7-3 is an extension of Fig. 7-2 in which a Circadian rhythm node is introduced. In Chapter 3, we reviewed that two major causes of sleep are sleep-debt and circadian rhythm. Although we have only considered sleep-deprivation level in our experiment, circadian rhythm certainly affects task performance [36, 48, 93, 122, 122, 133] and is included as another parent node of each task performance. Thus, this model is a bi-partite structure with two parent nodes for each task performance. As in Fig. 7-2, each task performance is directly affected by sleep-deprivation level and circadian rhythm. Tasks are conditionally independent given the state of sleep-deprivation level and circadian rhythm.

We can expand the bi-partite model shown in Fig. 7-3 by introducing Drowsiness node in between the two sleep-causes and the task performances. Fig. 7-4 presents the expanded model. The Drowsiness node is defined as a representation of the drivers' mental state or feeling; it is an unobservable and uncontrollable state. Drowsiness is a child node of the Sleep-deprivation and Circadian rhythm nodes. At the same time, Drowsiness is the only parent node of each task performance. This structure is basically same as the model depicted in Fig. 7-3, but the introduction of the intermediate node, Drowsiness, allows a reduction in the number of conditional probability tables necessary to form a model. We have a total of $2n$ links between nodes in Fig. 7-3 and only $n + 2$ in Fig. 7-4.

Table 7.1: Conditional Probability Table

Stimulus-response tasks

parent node	APVT		VPVT		SLCT		DLCT	
	T_{APVT}	F_{APVT}	T_{VPVT}	F_{VPVT}	T_{SLCT}	F_{SLCT}	T_{DLCT}	F_{DLCT}
T	0.571	0.429	0.571	0.429	0.357	0.643	0.571	0.429
F	0.357	0.643	0.500	0.500	0.214	0.786	0.357	0.643

Tracking tasks

parent node	LT		LT		WG		SC		CL	
	T_{LT}	F_{LT}	T_{LV}	F_{LV}	T_{WG}	F_{WG}	T_{SC}	F_{SC}	T_{CL}	F_{CL}
T	0.500	0.500	0.286	0.714	0.571	0.429	0.429	0.571	0.500	0.500
F	0.357	0.643	0.286	0.714	0.286	0.714	0.286	0.714	0.357	0.643

Quantitative component of the SBN

Once the topology of the Bayesian network is laid out, a CPT (Conditional Probability Table) for the each node is required to complete the formulation of BN. In order to directly utilize our experimental data and to simplify the model, we adopt the bi-partite model presented in Fig. 7-2 from now on.

Since all subjects have participated in two sessions with different sleep-deprivation levels, we can obtain a full CPT directly from the experiment. In this case, we assume all nodes are Boolean, i.e. Sleep-deprivation is either *no sleep-deprivation* or *partial sleep-deprivation* and each task performance is either *lapse* (bad, degraded) or *no-lapse* (good, normal). We use the following formula to estimate each conditional probability [59].

$$p(B|A) \approx \frac{Num.(B = \text{true} \cap A = \text{true}) + 1}{Num.(A = \text{true}) + 2} \tag{7.1}$$

$$p(B|\neg A) \approx \frac{Num.(B = \text{true} \cap A = \text{false}) + 1}{Num.(A = \text{false}) + 2} \tag{7.2}$$

To obtain an estimate of the probability that B is true given that A is true, we count the number of cases in which A and B are both true, and divide by the number of cases in which A is true. The probability of B is true given A is false can be estimated in a same way. Since we deal with experimental data, we apply Bayesian correction

Table 7.2: Estimated probability of sleep-deprivation based on each task performance

Successful Alarm		False Alarm	
$p(T\|T_{APVT})$	0.6154	$p(T\|F_{APVT})$	0.4000
$p(T\|T_{VPVT})$	0.5333	$p(T\|F_{VPVT})$	0.4615
$p(T\|T_{SLCT})$	0.6250	$p(T\|F_{SLCT})$	0.4500
$p(T\|T_{DLCT})$	0.6154	$p(T\|F_{DLCT})$	0.4000
$p(T\|T_{LT})$	0.5833	$p(T\|F_{LT})$	0.4375
$p(T\|T_{LV})$	0.5000	$p(T\|F_{LV})$	0.5000
$p(T\|T_{WG})$	0.6667	$p(T\|F_{WG})$	0.3750
$p(T\|T_{CS})$	0.6000	$p(T\|F_{CS})$	0.4444
$p(T\|T_{CL})$	0.5833	$p(T\|F_{CL})$	0.4375

[59] to our estimates. Thus, we add 1 to the count in the numerator, and 2 (since we have binary variables) to the denominator.

We define states of the sleep-deprivation node as T = partial sleep-deprivation and F = no sleep-deprivation. For stimulus-response tasks, the true state of each task is defined to occur when $\mathrm{RT}_{task_i} \geq \theta_{task_i}$, where θ_{task_i} is a pre-set threshold for $task_i$. For tracking tasks, the true state is defined to occur when $\mathrm{RMT}_{task_j} \geq \theta_{task_j}$, where θ_{task_j} is a pre-set threshold for $task_j$. For example, T_{APVT} means $\mathrm{RT}_{APVT} \geq \theta_{APVT}$. Accordingly, the false state F_{APVT} is when $\mathrm{RT}_{APVT} < \theta_{APVT}$.

The threshold θ should be carefully set, and thus the effect of various threshold values on the model is discussed in Section 7.2.2. We first examine one example case for an arbitrary threshold. The Conditional Probability Table (CPT) for each task node is shown in Table 7.1. The thresholds θ for stimulus-response are set at the mean RT (or RMT) value of non-sleep-deprived drivers plus 50% of STD of the drivers: $\theta_{APVT} = 0.865$ sec, $\theta_{VPVT} = 1.032$ sec, $\theta_{SLCT} = 0.812$ sec, and $\theta_{DLCT} = 0.771$ sec. For tracking tasks, the CPT is calculated from RMT when sampling length $= 350m$ and RMT threshold $\alpha = 20\%$. For Sleep-deprivation node, $p(T) = p(F) = 0.5$ since we have equal numbers of both non and partially sleep-deprived sessions.

7.2.2 Simulation Results via Experimental Data

We have formulated a full SBN for drowsy driver detection based on driver-vehicle data. In this section, we discuss the SBN performance, inferences of driver alertness

Table 7.3: Estimated probability of sleep-deprivation based on multiple task performances

Successful Alarm		False Alarm	
$p(T\|T_{APVT,VPVT})$	0.6465	$p(T\|F_{APVT,VPVT})$	0.3636
$p(T\|T_{APVT,SLCT})$	0.7273	$p(T\|F_{APVT,SLCT})$	0.3529
$p(T\|T_{APVT,DLCT})$	0.7191	$p(T\|F_{APVT,DLCT})$	0.3077
$p(T\|T_{VPVT,SLCT})$	0.6557	$p(T\|F_{VPVT,SLCT})$	0.4122
$p(T\|T_{VPVT,DLCT})$	0.6465	$p(T\|F_{VPVT,DLCT})$	0.3636
$p(T\|T_{SLCT,DLCT})$	0.7273	$p(T\|F_{SLCT,DLCT})$	0.3529
$p(T\|T_{APVT,VPVT,SLCT})$	0.7529	$p(T\|F_{APVT,VPVT,SLCT})$	0.3186
$p(T\|T_{APVT,SLCT,DLCT})$	0.7453	$p(T\|F_{APVT,SLCT,DLCT})$	0.2759
$p(T\|T_{APVT,SLCT,DLCT})$	0.8101	$p(T\|F_{APVT,SLCT,DLCT})$	0.2667
$p(T\|T_{VPVT,SLCT,DLCT})$	0.7529	$p(T\|F_{VPVT,SLCT,DLCT})$	0.3186
$p(T\|T_{APVT,VPVT,SLCT,DLCT})$	0.8298	$p(T\|F_{APVT,VPVT,SLCT,DLCT})$	0.2376

states based on driver-vehicle data. We also analyze results when we have various threshold values θ defined in the previous section.

Successful Alarm and False Alarm

We first examine positive and negative outcomes of the inference based on the driving performance, i.e., driver-vehicle data. Successful Alarm (SA) is a positive and False Alarm (FA) is a negative consequence of the inference. Table 7.2 shows both SA and FA when performance of only one task is considered.

We can also calculate the inference when we have multiple performance of tasks. Table 7.3 shows the inference probability when we only consider combinations between stimulus-response tasks.

Table 7.3 clearly shows the trend that if a driver performs badly in multiple tasks, the probability of that driver being sleep-deprived $p(SD)$ increases. We can observe this in the first two columns of the Table. At the same time, $p(SD)$ decreases when a driver shows good performance in multiple tasks, shown in last two columns of the Table.

We pre-defined lapse thresholds when we computed the CPT. These threshold values directly affect the CPT and inference probabilities (SA and FA), and thus we should examine effects of the lapse threshold on the CPT, SA, and FA. We first examine the CPT for various threshold values. Fig. 7-5 shows each component of the

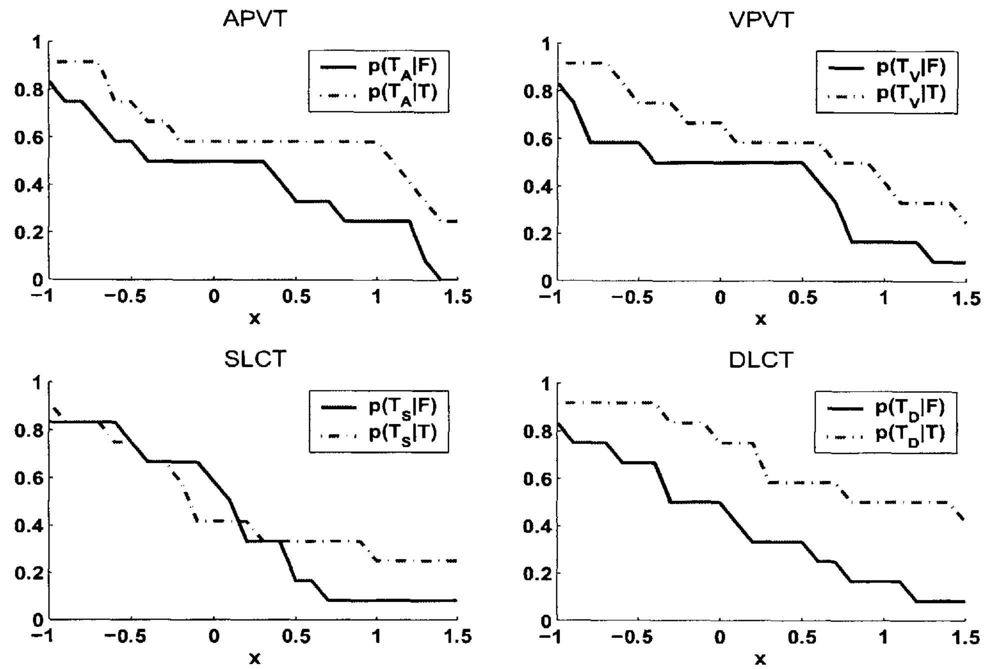

Figure 7-5: Threshold vs. conditional probabilities: threshold = x·STD + Mean of non-sleep-deprived drivers

CPT, i.e. $p(T_{Task}|T)$ and $p(T_{Task}|F)$, as threshold values vary for each task. The threshold θ_{task_i} varies from the mean value of non-sleep-deprived drivers minus 100% of STD, to the mean plus 150% of STD. Values of all components of the CPT decrease when the threshold value increases. Lapse thresholds need to be set at a level such that the difference between each $p(T_{Task}|T)$ and $p(T_{Task}|F)$ is noticeable. We have examined one example with a fixed threshold in this section, the mean plus 50% of STD.

We now investigate both SA and FA for various threshold values. The System Operating Characteristic (SOC) curve [70] is introduced to study trade-offs between the probabilities as the threshold varies.

An SOC curve is shown in Figure 7-6, where SA and FA from the different lapse thresholds based on a single task are presented: $p(T|T_{APVT})$ and $p(T|F_{APVT})$, $p(T|T_{VPVT})$ and $p(T|F_{VPVT})$, $p(T|T_{SLCT})$ and $p(T|F_{SLCT})$, and $p(T|T_{DLCT})$ and $p(T|F_{DLCT})$. The thresholds varied from the mean value of non-sleep-deprived drivers minus 100% of STD to the mean plus 150% of STD. The SOC of SLCT did not perform as promisingly as that of APVT, VPVT, or DLCT (with more FA and less SA

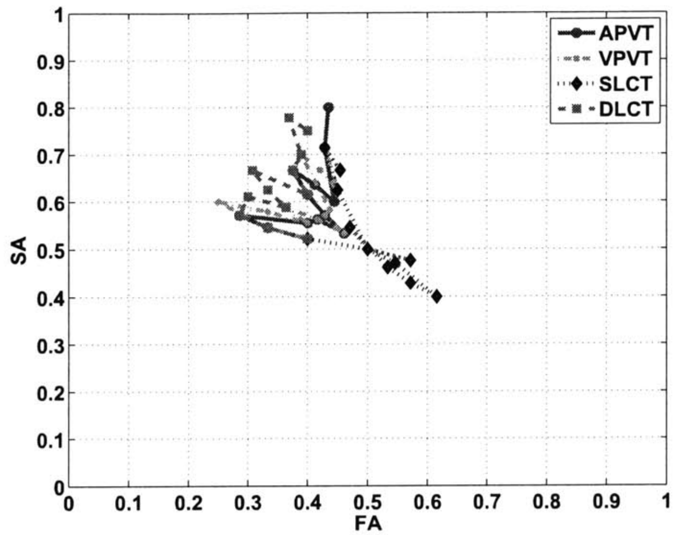

Figure 7-6: SOC curve of stimulus-response tasks

than other tasks). However, if we pick a threshold greater than approximately +50% of STD, we notice that SLCT gives a good performance as well (Table 7.2 and Table 7.3).

Thus, we need to consider SA, FA, *and* CPT to determine an optimal lapse threshold.

Individual SOC Curves

We can also formulate SBN for each individual subject. The topology of an individual SBN is same as we have adopted. However, the CPT should be estimated from experiments of each subject. Fig. 7-7 and 7-8 show SOC curves from subject #9 and #10 respectively. Each of them is different from the SOC curve shown in Fig. 7-6, and each has its own shape. For subject #9, SOC curves for all stimulus-response tasks overlap very much in the middle of the domain. This implies that all stimulus-response tasks examined in the experiment are insensitive to sleep-deprivation for subject #9. However, for subject #10, APVT provides a superior drowsiness index relative to all other tasks. SOC curves from the rest of subjects are shown in Appendix B.2. We observe that each individual has their own characteristics (distinguishable SOC curves).

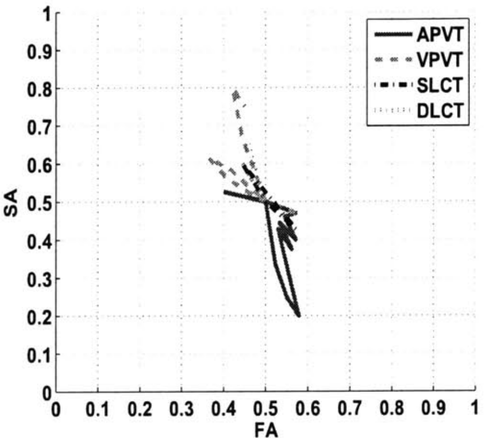

Figure 7-7: SOC curve: Subject #9

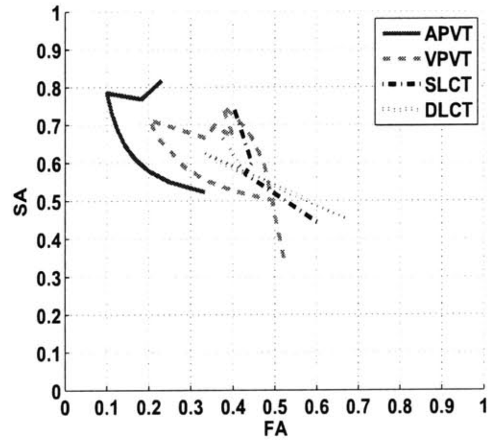

Figure 7-8: SOC curve: Subject #10

7.3 Dynamic Bayesian Networks

We have investigated Static Bayesian networks mainly considering causality between variables, but we have not examined temporal aspects of the drowsy driver detection problems. Drowsiness is cause by either sleep-deprivation or circadian rhythm; many other environmental factors such as boredom or motivation can mask/unmask sleepiness as well (Chapter 3). Thus, drowsiness definitely possesses a time-dependent characteristic, and the temporal aspect should be considered in the detection modeling.

Dynamic Bayesian networks (DBNs) are directed graphical models of stochastic processes. They generalize Hidden Markov models (HMMs) and linear dynamical systems (LDSs) by representing the hidden and observed states in terms of state variables, which can have complex interdependencies. The graphical structure provides an easy way to specify these conditional independencies and hence provides a compact parameterization of the model [90, 91]. (*Temporal* Bayesian network would be a better name than *Dynamic* Bayesian network, since it is assumed that the model structure does not change, but the term DBN has become entrenched.)

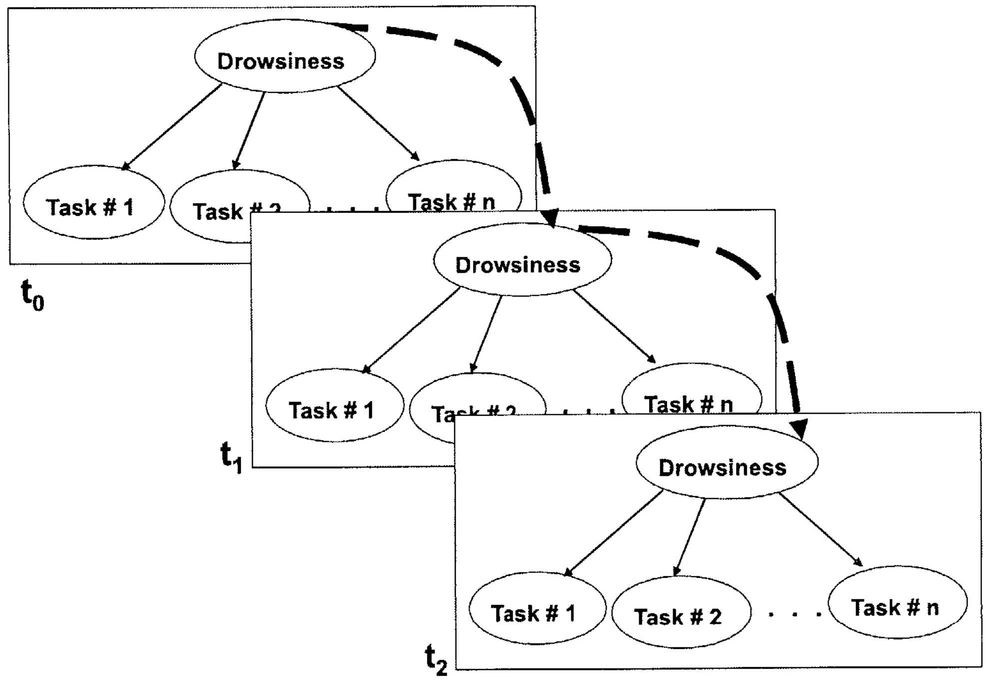

Figure 7-9: Temporal model of drowsiness detection problems

7.3.1 Formulation of DBN

Working with domains that evolve over time, we can introduce a discrete time stamp and have a model for each unit of time. We call such a local model a *time slice.* The time slices are connected through *temporal links* to constitute a full model. If the structure of the time slices is identical, and if the temporal links are the same, we say that the model is a *repetitive* temporal model. If the conditional probabilities also are identical, we call the model *strictly* repetitive [53]. We assume a DBN for drowsy driver detection problem is strictly repetitive.

Topology of the DBN

In Fig. 7-9, each time slice at t_0, t_1, t_2 is contained in a square box. The topology of each time slice is identical to the SBN introduced in Fig. 7-2. However, in each time slice, we have a Drowsiness node instead of a Sleep-deprivation node; the Drowsiness node implicitly includes both sleep-deprivation and circadian rhythm. In order to capture the temporal aspects of drowsiness, we need to introduce a link between each time slice. The temporal link is shown in a dashed line in Fig. 7-9. The structure can

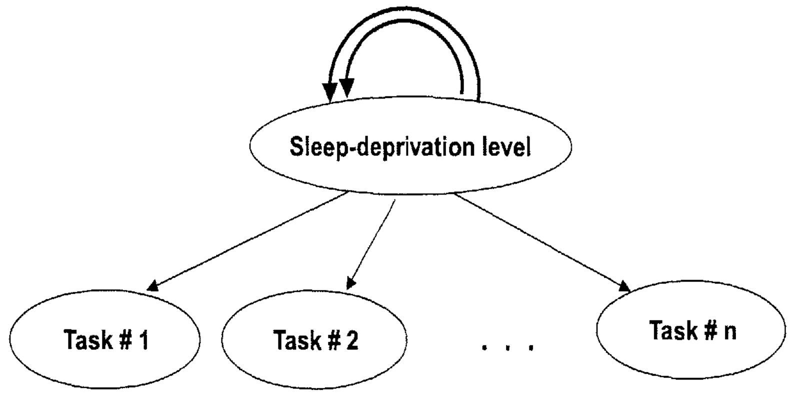

Figure 7-10: A compact specification of the model in Fig. 7-9

be depicted compactly in Fig. 7-10; the double arrow ($\Longrightarrow$) indicates a temporal link from time slice t to slice $t+1$.

Quantitative component of the DBN

Since we assume the DBN is strictly repetitive, we only need to specify the transition model for the temporal link, i.e., $p(X_{t+1}|X_t)$. (We assume that each time slice is identical to the SBN specified in the previous section. Thus, conditional probabilities within each time slice can directly adopted from the CPT of the SBN.) Since we do not have experimental data on the temporal aspects of drowsiness, we need to estimate the transition model from previous studies. It has been noted that drowsiness or sleepiness has a "sleep inertia", that makes drowsiness continue once it happens [44]. This fact suggests to us that the transition probability $p(X_{t+1}|X_t)$ should not be small, although we do not know the exact transition probability. Thus, the following analysis deals with various values of $p(\text{Drowsiness}_{t+1}|\text{Drowsiness}_t)$ and $p(\text{Non-drowsiness}_{t+1}|\text{Non-drowsiness}_t)$.

7.3.2 Simulation Results via Experimental Data

Assuming that each time slice corresponds to the moment when any task is performed, we can first infer the driver drowsiness (or alertness) states based on repetitive performances of each task. Fig. 7-11 and Fig. 7-12 show the estimated probabilities from the DBN. Since our experiments have examined APVT and VPVT 10 times per

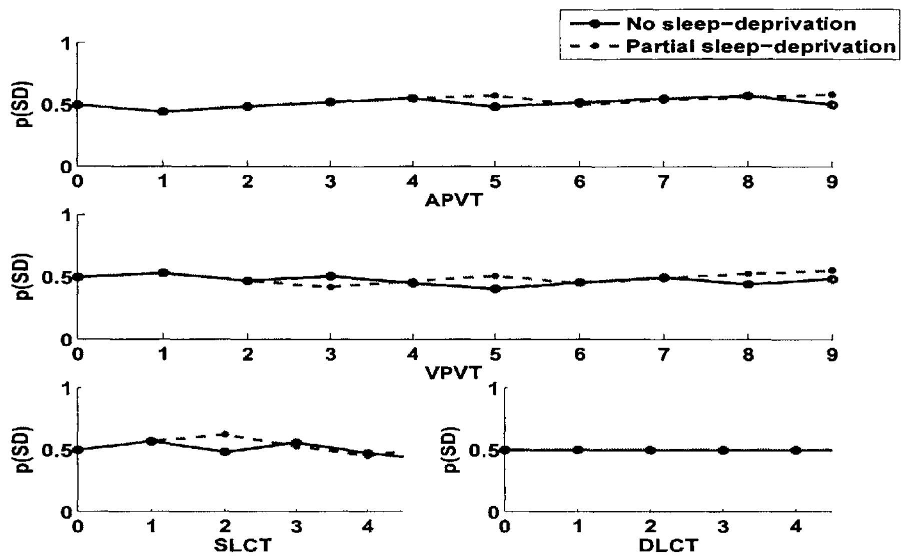

Figure 7-11: DBN inference: Subject #9

session, we have 10 time slices for APVT and VPVT. SLCT and DLCT have only 5 time slices. Each figure has data from non and partially sleep-deprived groups shown in solid and dashed lines, respectively. The lines indicate the probability of drivers being sleep-deprived based on the evidence for each time slice. For subject #9, it is almost impossible to differentiate driver alertness states based on stimulus-response tasks. However for subject #10, we can distinguish driver alertness states based on APVT, VPVT, and DLCT performances.

Based on the inference results, we can divide subjects into two groups: a group whose inference results based on driver performances are satisfactory and a group whose results are *not* satisfactory. The satisfactory result means that the estimated probability $p(SD)$ from non and partially sleep-deprived groups is clearly differentiable. For example, Subject #9 (shown in Fig. 7-11) is an example of a non-differentiable subject, whereas Subject #10 (shown in Fig. 7-11) is differentiable. For majority of subjects (9 out of 12 subjects), inferring driver alertness states based on driving performance is possible. However, for the rest of the subjects, driver-vehicle data (driving performance) may not be good enough to infer their alertness states.

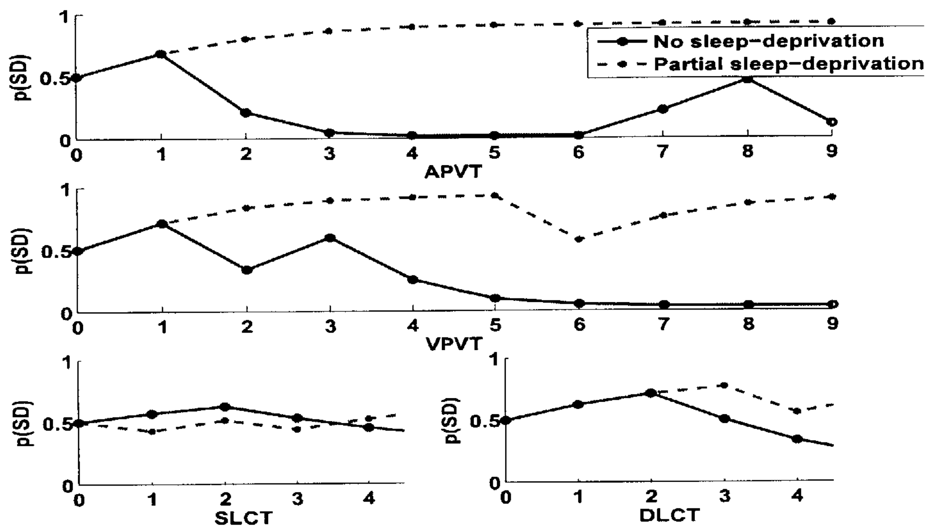

Figure 7-12: DBN inference: Subject #10

7.4 Guidelines for Designing Drowsy Driver Detection Systems

We have comprehensively analyzed characteristics of sleep-deprived drivers through a simulator-based human-in-the-loop experiment in Chapter 5. In this Chapter, we have provided inferences of driver alertness based on the BN paradigm and the experimental data. Based on drowsy driving characteristics along with the simulated inference results, we propose the following for further directions of design of drowsy driver detection systems.

- **Monitoring driver-vehicle allows drowsy driving detection, and further studies on varied driving tasks are necessary.** The simulation results shown in Section 7.2 and 7.3 demonstrate that drowsy driver detection based on driver performance is *feasible*. By examining various driving tasks, we have been able to differentiate driver alertness states; estimated probabilities of drivers being sleep deprived $p(SD)$ show obvious differences for most subjects based on performance of non- and partially sleep-deprived drivers. Thus, we claim that further studies on driver-vehicle data should be continued for developing drowsy driver detection systems.

- **Not all tasks are equally sensitive to drowsy driving.** In our experimental data, we have observed that drowsiness has a greater effect on rule-based tasks than on skill-based tasks. In Section 7.2 and 7.3, we confirm the findings by inferring driver alertness states using the BN paradigm. Thus, we suggest that driving performance of rule-based tasks should be more carefully investigated for an effective design of drowsy driver detection systems. Rule-based tasks we examined in the experiment were reaction time tasks (Psychomotor Vigilance Tasks) and tracking tasks with unexpected disturbances. Other rule-based tasks such as stopping at traffic signals should be examined. Skill-based tasks - which cover most driving tasks - should also be considered in the detection system. Although they cannot be used as early indicators of drowsy driving, deterioration of such tasks may indicate existence of other driving impairments such as inebriation.

- **Individual or group differences need to be considered in the design.** We have found statistically significant differences between non and partially sleep-deprived groups in the sample population. However, individual subjects exhibit their own characteristics. Each individual has different tasks sensitive to drowsiness. Some sleep-deprived drivers actually performed better or as well as in a non-sleep-deprived condition. We suggest further study to determine whether other observations (physical changes, physiological signals, etc) provide distinctive information for these subjects. Furthermore, how other factors such as boredom or motivation can affect sleep-deprived drivers should be studied at the same time; how to deal with the drivers with high motivation, how long they can mask their drowsiness, can we consider the masked state safe, etc. We also suggest investigation of group characteristics, for groups divided by age, gender, proficiency, or cautiousness. For example, it has been known that younger and older drivers learn to use new systems differently. Older drivers have been shown to be distracted from the driving task when the cause of the warning was not clearly evident. In contrast, younger operators, by definition with fewer years of driving experience, were shown to have more trust in warning systems, often choosing to rely on the system alone rather than using it as a driver assist [26, 86]. This type of information should be considered in the design of drowsy driver detection systems. We have also reviewed in Chapter 2 that there are high-risk population groups for drowsy driving. Their group characteristics may be useful for designing drowsy driver detection systems.

- **Collaborations between policy makers and research engineers are essential.** Considering the nature of fatigue problems in automobiles, we suggest that systematic countermeasure development is crucial. For example, if we want to utilize the BN paradigm in the vehicle, we first need to have a priori information of drivers to set up the BN. Drivers' information may be able to obtained systematically through fatigue-related public policies or regulations. For example, we may consider including fatigue-related tests for commercial drivers along with their training processes. The information obtained from the test may provide driver characteristics necessary for the implementation of individualized detection systems. Drivers are poor judges of their own condition - others should be involved in the determination of whether a driver is adequately rested [47]. Thus, we stress the importance of systematic collaborations between policy makers and research engineers for effective fatigue management in automobiles.

Chapter 8

Conclusions and Future Work

In this thesis we have identified characteristics of drowsy driving and devised a systematic way to infer the state of driver alertness based on driver-vehicle data. Simulator-based human-in-the-loop experiments have not only shown a danger of drowsy driving, but have also revealed drowsy driving characteristics. Identification of drowsy driving characteristics and analysis of the sleep-wake cycle mechanism have laid the foundation for the systematic development of detection systems. Inferences of driver alertness states utilizing the BN paradigm and experimental data have confirmed that although detection techniques are essential the ultimate challenge lies in the human. A wide spectrum of human individual characteristics should be addressed in the design of drowsy driver detection systems. We encourage collaborations between policy makers and research engineers for managing fatigue problems in transportation effectively.

In this Chapter we summarize each part of the thesis, then present ideas for further research.

8.1 Summary

In Chapter 2, we have extensively reviewed research on fatigue management in transportation systems, including on-going research projects in the U.S.A and Europe. We have examined existing measures of drowsy driving from the point of view of transportation policies and detection technique, and investigated drowsy driving detection techniques in three different categories: by physiological signals, by physical changes of drivers, and by driver-vehicle data. Then, statistics and some known facts of drowsy driving have been presented, including crash characteristics and high-risk population groups in drowsy driving. It has been shown that fatigue management in transportation is a very active and critical research area.

In Chapter 3, we have reviewed the mechanism of the human sleep-wake cycle along with causes of sleep. Contrary to common belief that sleep is a passive state caused by a decrease in a stimulus level to human, we have presented recent exposition that sleep is indeed an active state of the brain and is involuntary. The reticular formation and the hypothalamus are key regulators of sleep and wakefulness. The circadian pacemaker and homeostasis are two primary neurobiological forces that govern the sleep-wake cycle. However, boredom and environmental factors such as noise, light, and stress just mask or unmask sleep. We have briefly reviewed the physiology of sleep-wake regulation, introduced EEG signal patterns and REM/NREM sleep along with age effect, and provided definitions of related terminologies and examples of subjective assessments of sleepiness. This Chapter provides in-depth description of the characteristics of drowsiness.

In Chapter 4, we have studied driver-vehicle systems in general and investigated well-defined and ill-defined components of driver-vehicle systems. We have reviewed various types of inputs to driver-vehicle systems, such as visual, vestibular, auditory, and tactile inputs, and we have analyzed control interface of driver-vehicle systems including steering and throttle/brake control as well. Finally, simplified longitudinal and lateral vehicle dynamics have been presented. This Chapter is oriented toward understanding general characteristics of driving and of driver-vehicle systems.

In Chapter 5, we have designed and performed human-in-the-loop experiments using a fixed-based driving simulator, aiming to identify valid drowsy driving characteristics. We have clearly stated our experimental objectives and a hypothesis that drowsiness affects various driving tasks non-uniformly, inspired by brain functions related to the human motor control system and the sleep-wake cycle regulators. Design of experiments including the assignment of independent and dependent variables, have been delineated in detail. We have controlled sleep-deprivation levels of drivers before each experiment session and examined a myriad of driving/non-driving tasks during the experiment. STISIM has been utilized as a fixed-based driving simulator, and a detailed experimental set-up has been described as well. A total of twelve subjects have participated in both non-sleep-deprived and partially-sleep-deprived sessions. This Chapter provides the detailed methodology of identifying characteristics of drowsy driving.

In Chapter 6, we have extensively analyzed the driver-vehicle data obtained from the experiments described in Chapter 5. Studying with-in subject performance differences between two different sleep-deprivation levels for various driving tasks, we have used non-parametric statistical tests to determine the existence of significant differences between two groups. In terms of lateral lane tracking errors, we have been able to see the significant performance degradation in partially-sleep-deprived groups for the wind gust condition, change in steering dynamics, and curvy roads. However, our data showed negligible performance differences in lane tracking errors with no disturbances on straight road and with a lead vehicle in front of the drivers. Most stimulus-response tasks have showed significant performance degradation as well; Auditory Psychomotor Vigilance Tasks, Visual Psychomotor Vigilance Tasks, and Double Lane Change Tasks were affected. However, our analyses have showed little performance degradation in Single Lane Change Tasks. This suggests that under sleep deprivation, performance in rule-based tasks deteriorates to a greater extent than that in skill-based tasks. Corresponding analysis on order effects and power analysis have been discussed as well. The Crossover Model has been applied to both Single and Double Lane Change Tasks to understand them as continuous tracking tasks rather than discrete stimulus-response tasks, which has also provided consistent outcomes. This Chapter contributes to the identification of the characteristics of drowsy driving.

Finally, in Chapter 7 we have devised a systematic way to detect human drowsiness. The Bayesian network paradigm has been introduced, along with its basic concepts including d-separation. We have configured a topology of a Static BN for drowsy driver detection based on driver-vehicle data. Quantitative components of a Static BN have been extracted from the experimental data. Inference of driver alertness states from the Static BN have been calculated and summarized in both tabular forms and SOC curves. Then, a Dynamic BN has been introduced to capture temporal aspects of drowsiness. It has been shown that individual subject characteristics should be addressed when designing drowsiness detection systems, although overall sample trends in performance degradation have been found and overall inference results have shown non-trivial results. This Chapter provides a systematic methodology to detect drowsy drivers, and motivates future research on detection of drowsy driving.

8.2 Future Work

8.2.1 In-Vehicle Application

We have shown that drowsy driver detection is feasible based on driver-vehicle data. However, there are many obstacles to overcome, which motivates further supportive research. First, reliability and validity of the technique should be improved for real-world application. Experiments using the protocol presented in Chapter 5 need to be extended to motion-based simulators and field tests to fully consider all influences to drivers such as vestibular sensory inputs. Secondly, collaborative research between public policy makers and research engineers should follow. For example, we may consider including fatigue-related tests for commercial drivers along with their training processes. The information obtained from the test may provide driver characteristics necessary for the implementation of individualized detection systems.

8.2.2 General Driver Monitoring Systems

We can extend the drowsy driver detection methodology to detection of other driving impairments. Once we understand the characteristics of impaired driving under the influence of alcohol, motion-sickness, stress, or inattention, we can extend the drowsy driver detection method introduced in Chapter 7 to general impaired driving detection

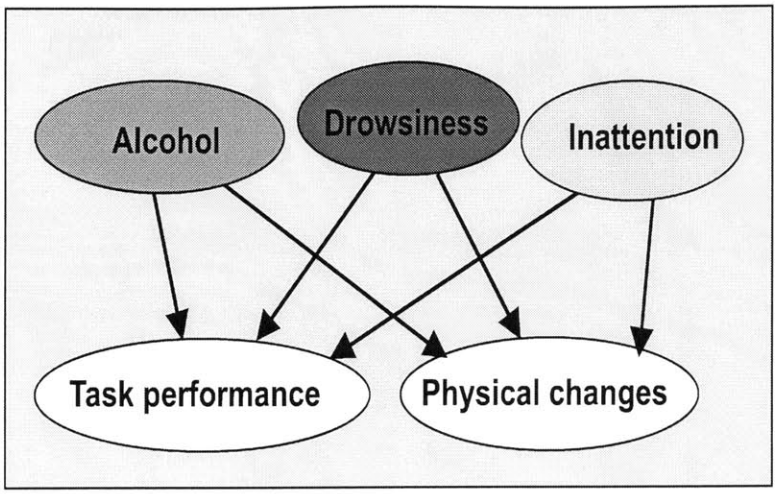

Figure 8-1: Detection of impaired drivers

systems. For example, we can include the associated nodes for each impaired driving condition in the BN structure to precisely assess the driver's state. Fig. 8-1 shows an extended version of Fig. 7-2 including alcohol and inattention nodes as other possible causes of impaired driving. We expect each impaired driving state to possess distinct characteristics. For example, it is known that the alcohol influences the function of the cerebellum, whereas drowsiness affects the function of the basal ganglia more than that of the cerebellum. This fact suggests that the resulting performance degradation from each different driving impairment should show different characteristics. We also need to precisely develop dynamic BN models to fully consider circadian rhythm and other temporal aspects of drowsiness.

8.2.3 Higher-Level Complex Tasks

The experiments in Chapter 5 have covered a variety of rule-based and skill-based tasks, which represent tasks typically required for driving. However, some driving-related tasks such as path-planning or navigation should be considered as knowledge-based tasks since they involve more cognitive resources and higher-level functions of the brain. We may need to accommodate new factors such as motivation or boredom to fully deal with high-level cognitive tasks. Research on high-level cognitive tasks would provide in-depth understanding of fatigue problems in general. Human ability is known to be very robust, yet is affected by a myriad of different circumstances. Collaborations among engineering, neuroscience, and human factors are necessary for this study.

8.2.4 Fatigue Management in Various Transportations

There is no doubt that automobiles are the most prevalent form of transportation in most countries. However, it has been noted that accidents caused by fatigue in other areas of transportation such as aviation, marine-transportation, railroads, and in other industrial areas are severe [74, 119]. Because fatigue management research has been performed in many other areas, active collaborations between these groups are highly recommended. Each transportation method has its own dynamics and characteristics. Hence, the fatigue management method should be specialized distinctly to enhance the safety of each transportation mode.

8.2.5 Countermeasure Development

Although detection and counteraction of drowsy driving are two different problems, there is no doubt that they are closely linked together. We need to develop effective countermeasures for drowsy driving along with more reliable detection techniques. Some previous research on fatigue countermeasures from both a policy and a technical standpoint can be found in [1, 18, 62, 75, 79, 102, 119] The countermeasures can be grouped into *alarm* or *alert maintainers* [79]; alarms are activated only after some degree of driver alertness has be lost, and alert maintainers are designed in the hope that the required level of alertness for safe driving will not be lost. For example, effectiveness of various alarm modalities such as visual, auditory, tactile, or thermal would be important to develop countermeasures for drowsy driving.

Appendix A

Experiment Design

A.1 Experiment Scenario Programming

The contents of this section except programming codes are directly quoted from STISIM help documents [109, 124].

Driving tasks and scenarios are easily specified with simple commands listed in an events file. A simple Scenario Definition Language (SDL) has been developed by Systems Technology Inc. to minimize the effort required to specify experimental designs. Open Module Programming (OMP) provides the user with a means of extending the capabilities of the STISIM Driving simulator beyond what has been provided by Systems Technology Inc.

The following script is an example of SDL script used in the experiment for Subject #2. Definition of each event shown in the code follows.

An Example of SDL script for Subject #2

```
METRIC
0, BSAV, 1, .03, Experiment Data, 1, 39, 7, 6, 4, 5, 2, 3, 10, 24, 30, 31, 11, 26, 27, 28,
42, 40, 9, 19
0, ROAD, 5, 4, 3, 1, 0.15, 3, 3, 0.15, 0.15, 0, -1, -1, 0, 10, 0, 10, -5, 3, -5, 3, 0
0, OM, 1, 0
50, TREE, 70, 0, *1~18;-4;-15, 25, 30, 0
20105, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_01.LMM
20440, OM, 1, 0
```

```
21140, OM, 1, 1
23040, OM, 1, 0
23594, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
23809, DA, 1, 0, 0, .5; .7;
24194, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_03.LMM
24527, DA, 1, 0, 0, .5; .7;
24812, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
25071, WG, 1, 0, 4
26112, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
26335, DA, 1, 0, 0, .5; .7;
26550, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
26872, WG, 1, 0, 4
27915, DA, 1, 0, 0, .5; .7;
28977, DA, 1, 0, 0, .5; .7;
29275, DA, 1, 0, 0, .5; .7;
29674, C, 150, 20, 120, 20, 0.002
29974, C, 150, 20, 120, 20, -0.003
30144, C, 150, 20, 120, 20, 0.001
30314, C, 150, 20, 120, 20, -0.004
30514, C, 150, 20, 120, 20, 0.005
30704, C, 150, 20, 120, 20, -0.003
30904, C, 150, 20, 120, 20, 0.002
31169, FLLW, 22, 100, 0{5}, 12, 10, 2, 100, C:\STISIM\Jihyun\Data\SpeedProfile.Sin, 1, 0, 10
34207, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_02.LMM
34452, OM, 1, 0
35152, OM, 1, 1
37052, OM, 1, 0
37966, FLLW, 22, 100, 0{5}, 12, 10, 2, 100, C:\STISIM\Jihyun\Data\SpeedProfile.Sin, 1, 0, 10
41080, WG, 1, 0, 4
42217, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
42480, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
42733, DA, 1, 0, 0, .5; .7;
43006, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_03.LMM
43316, DA, 1, 0, 0, .5; .7;
43609, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_01.LMM
43915, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
44195, OM, 1, 0
44895, OM, 1, 1
```

```
46795, OM, 1, 0
47265, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
47515, DA, 1, 0, 0, .5; .7;
47780, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_02.LMM
48063, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_03.LMM
48365, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
48579, DA, 1, 0, 0, .5; .7;
48995, PR, C:\STISIM\SOUND\RINGIN.WAV, 0, 10
49256, FLLW, 22, 100, 0{5}, 12, 10, 2, 100, C:\STISIM\Jihyun\Data\SpeedProfile.Sin, 1, 0, 10
52396, C, 150, 20, 120, 20, 0.002
52696, C, 150, 20, 120, 20, -0.003
52866, C, 150, 20, 120, 20, 0.001
53036, C, 150, 20, 120, 20, -0.004
53236, C, 150, 20, 120, 20, 0.005
53426, C, 150, 20, 120, 20, -0.003
53626, C, 150, 20, 120, 20, 0.002
53893, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_01.LMM
54215, C, 150, 20, 120, 20, 0.002
54515, C, 150, 20, 120, 20, -0.003
54685, C, 150, 20, 120, 20, 0.001
54855, C, 150, 20, 120, 20, -0.004
55055, C, 150, 20, 120, 20, 0.005
55245, C, 150, 20, 120, 20, -0.003
55445, C, 150, 20, 120, 20, 0.002
55925, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_03.LMM
56181, SOBJ, 100, 5, 0,0,0,0, C:\STISIM\Data\Signs\Sngl_OvrHd_02.LMM
56589, V, 27, 100, 0{5}, 1, 2, 57289{15}, 0, 0, 2
90000, ES
```

The event files has a floating file format, this means that each line of the file does not have the same number of parameters in them. The general format for each line of the file is:

ON DISTANCE, EVENT SPECIFIER, PARAMETER 1,..., PARAMETER N

The *ON DISTANCE* parameter is the longitudinal distance down the road since the start of the simulation run that the driver has driven when the event will initially appear on the screen. The following explains each supported event used in our script. We use Metric unit for the script as shown in the first line thus the distance is in m.

Explanations of each event starts from *PARAMETER 1* and only includes what the previous script has.

BSAV - Begin saving dynamic data for the output file

PARAMETER 1 = 1; Save data based on the number of seconds that have elapsed since the last time the program saved an increment of data.
PARAMTEER 2 = .03; The save increment.
PARAMTEER 3 = Experiment Data; This is a string variable that allows us to mark a particular data block with its own individual title.
PARAMETER 4 = 1, 39, 7, 6, 4, 5, 2, 3, 10, 24, 30, 31, 11, 26, 27, 28, 42, 40, 9, 19; These parameters represent the data variables that we would like save.

1 = Elapsed time since the beginning of the run (seconds)

39 = Computer system time stamp in hours, minutes, seconds, and milliseconds. This allows the simulator data to be time synchronized with other computers

7 = Driver's lateral lane position with respect to the roadway dividing line, positive to the right (m)

6 = Total longitudinal distance that the driver has traveled since the beginning of the run (m)

4 = Driver's longitudinal velocity (m/s), 5 = Driver's lateral velocity (m/s)

2 = Driver's longitudinal acceleration (m/s^2)

3 = Driver's lateral acceleration (m/s^2)

10 = Vehicle heading angle (degrees)

24 = Vehicle yaw rate (radians/second)

30 = Total pitching angle, includes both ground slope and vehicle motion (radians)

31 = Total rolling angle, includes both ground slope and vehicle motion (radians)

11 = Steering wheel angle input (degrees)

26 = Steering input counts

27 = Throttle input counts,

28 = Braking input counts

42 = Current state of all of the input buttons

40 = Driver's response time (seconds) to any divided attention tasks

9 = Current roadway curvature (1/m)

19 = Roadway traffic data. For each vehicle that is in the roadway display, this parameter will save the following data: Vehicle identification number, Difference in longitudinal speed between the driver's vehicle and the roadway vehicle (m/s), Longitudinal position of the roadway vehicle with respect to the driver's vehicle (m), Lateral position of the roadway vehicle with respect to the roadway's dividing line (m)

C = Add curvature to the roadway display

PARAMETER 1 = 150; The longitudinal distance (m) that the beginning of the curve is away from the driver when the curve first appears.
PARAMETER 2 = 20; Entry spiral length (m).
PARAMETER 3 = 120; The longitudinal length of the curved section of roadway (m).
PARAMETER 4 = 20; Exit spiral length (m). An exit spiral is a transition section of roadway from a curve to a straight section of road.
PARAMETER 5 = { -0.004, -0.003, 0.001, 0.002, 0.004, or 0.005}; Constant roadway curvature (1/the radius of curvature, 1/m). A positive curvature means that the roadway will curve to the right while a negative value of curvatures means the roadway will curve to the left.

DA = Add a divided attention symbol to the display

PARAMETER 1 = 1; Left triangle symbol.

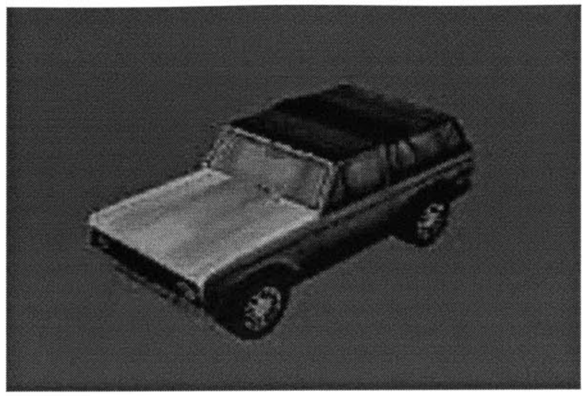

Figure A-1: Lead vehicle model type

PARAMETER 2 = 0; Driver is suppose to respond to symbols, all events will continue to appear whether the driver respond or not

PARAMETER 3 = 0; Volume control

PARAMETER 4 = 0.5; 0.7; Change the positioning of the symbol box. Left edge of the box = 0.5, top edge of the box= 0.7 where the screen is defined as left edge = 0, bottom edge = 0, right edge = 1, top edge = 1.

ES = End simulation run

End a simulation run.

FLLW = Follow a lead vehicle

PARAMETER 1 = 22; The initial speed, in m/s, of the lead vehicle that will be followed.

PARAMETER 2 = 100; The longitudinal distance, in m, that the lead vehicle is away from the driver when the lead vehicle initially appears.

PAREMETER 3 = 05; The lateral lane position, in m. 0 means lateral position of the object is specified with respect to the roadway dividing line.

PARAMETER 4 = 12; Lead vehicle model type number. Fig. A-1 shows the vehicle model used in the experiment.

PARAMETER 5 = 10; Time delay, in seconds, before the sine wave input kicks in.

PARAMETER 6 = 2; Gain on the lead vehicle's speed profile.

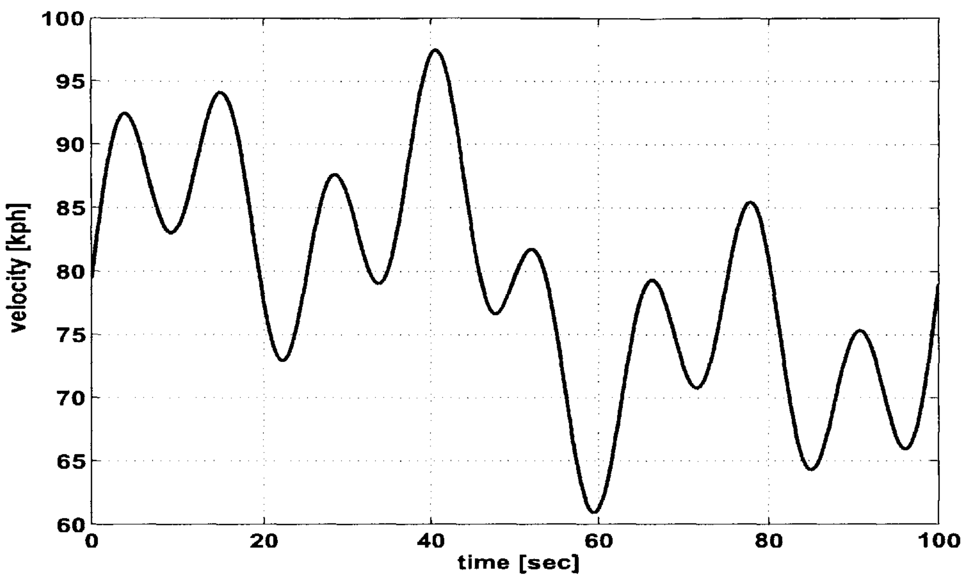

Figure A-2: Velocity profile of lead vehicle

PARAMETER 7 = 100; Length of time, in seconds, that the vehicle following task will be displayed.

PARAMETER 8 = `C:\STISIM\Jihyun\Data\SpeedProfile.Sin`; Name ans location of a file that contains the sinusoidal input profile. Fig. A-2 shows the velocity profile of the lead vehicle in kilometer per hour.

PARAMETER 9 = 1; Flag that specifies whether to save the raw data to the STISIM Drive data file.

PARAMETER 10 = 0; Warning distance (in m).

PARAMETER 11 = 10; Volume control

OM = Open Module

PARAMETER 1 = 1; Not used in the experiment.

PARAMETER 2 = 0 or 1; A default linear steering dynamics when 0 and a nonlinear steering dynamics when 1.

OM saves both the original steering input controlled by drivers and the modified (by backlash dynamics) steering input feed into the vehicle. The following is a part of the OM programming using Microsoft Visual Basic 6.0, which shows the backlash algorithm.

```
With Backlash
.Slope = 1#
.Cl = -2777.8
.Cr = 2777.8
End With
'
'
If ConvertedOMValue(1) = 1# Then
' Backlash
Backlash.Vl = NewSteering / Backlash.Slope + Backlash.Cl
Backlash.Vr = NewSteering / Backlash.Slope + Backlash.Cr

If Steering <= Backlash.Vl Then
NewSteering = Backlash.Slope * (Steering - Backlash.Cl)
Else
If Steering >= Backlash.Vr Then
NewSteering = Backlash.Slope * (Steering - Backlash.Cr)
Else
NewSteering = NewSteering
End If
End If
'
' Update Steering values
'
OrgSteering = Steering
Steering = NewSteering
Else
' When backlash off
If ConvertedOMValue(1) = 0# Then
OrgSteering = Steering
NewSteering = Steering
End If
'
OrgSteering = Steering
NewSteering = Steering
'
End If
```

```
'   Make the driver inputs available to the other methods
'
With Driver
    .Brake = Brake
    .Steer = Steering
    .Throttle = Throttle
    .Buttons = DInput
End With
'
'   Setup the return from function
'
ControlInputs = True
Exit Function
'
'   Handle any errors
'
ErrorOccurred:
'
ErrorMessage = ProcessError("ControlInputs")
ControlInputs = False
'
```

PR = Play recording

PARAMETER 1 = `C:\STISIM\SOUND\RINGIN.WAV`; The complete name of the file that contains the message to be played, including the path.
PARAMETER 2 = 0; Play the recording and continues to run the simulation
PARAMETER 3 = 10; Volume control.

ROAD = Display a specific roadway

PARAMETER 1 = 5; Width, in m, of each roadway lane.
PARAMETER 2 = 4; Total number of lanes that will be displayed.
PARAMETER 3 = 3; Total number of right hand side lanes.
PARAMETER 4 = 1; Roadway's dividing line striping option: dashed line.
PARAMETER 5 = 0.15; The distance, in m, from the edge of the roadway to the

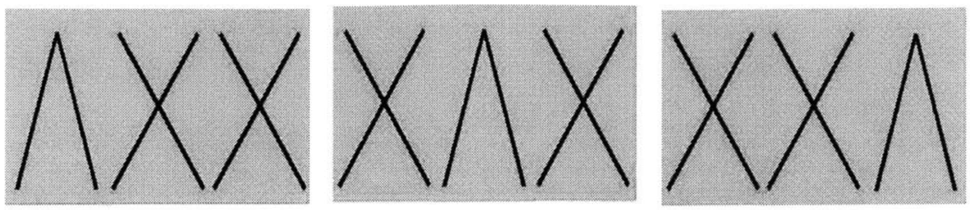

Figure A-3: Lane change jpeg images used for overhead signs

inside edge of the edge line.

PARAMETER 6 = 3; The length, in m, of the lane marker stripes.

PARAMETER 7 = 3; The longitudinal distance, in m, between the end of one stripe and the beginning of the next stripe.

PARAMETER 8 = 0.15; Width, in m, of the lane division markers.

PARAMETER 9 = 0.15; Width, in m, of the edge lines.

PARAMETER 10 = 0; Transition length, in m, to change from previous ROAD event.

PARAMETER 11 = -1; Cross-slope for the right hand side travel lanes, in percent grade. Negative values for the cross-slope mean that the road is sloping down as you go from the centerline to the roadway's outer edge.

PARAMETER 12 = -1; Cross-slope for the left hand side travel lanes, in percent grade. Negative values for the cross-slope mean that the road is sloping down as you go from the centerline to the roadway's outer edge.

PARAMETER 13 = 0; Cross-slope of the right hand side shoulder.

PARAMETER 14 = 10; Width, in m, of the right had side shoulder.

PARAMETER 15 = 0; Cross-slope of the left hand side shoulder.

PARAMETER 16 = 10; Width, in m, of the left had side shoulder.

PARAMETER 17 = -5; Slope of the right hand side foreslope, in percent grade.

PARAMETER 18 = 3; Width, in m, of the right hand side slope.

PARAMETER 19 = -5; Slope of the left hand side foreslope, in percent grade.

PARAMETER 20 = 3; Width, in m, of the left hand side slope.

PARAMETER 21 = 0; Width, in m, of the center median.

Figure A-4: Vehicle model for EM event

SOBJ = Add a static object

PARAMETER 1 = 100; The longitudinal distance, in m, that the static object is away form the driver when it first appears.
PARAMETER 2 = 5; Lateral position, in m, from the specified location to the bottom left corner of the static object.
PARAMETER 3 = 0; Height, in m, from the ground to the origin of the static object model.
PARAMETER 4 = 0; Rotation angle, in degrees, of the static object about its vertical axis.
PARAMETER 5 = 0; Rotation angle, in degrees, of the static object about its pitch axis.
PARAMETER 6 = 0; Rotation angle, in degrees, of the static object about its roll axis.
PARAMETER 7 = `C:\STISIM\Data\Signs\Sngl_OvrHd_02.LMM`; File name of the model file defining the static object. Fig. A-3 shows one of the overhead lane change signs used in the experiment.

TREE = Display trees on the side of the road

PARAMETER 1 = 70; Maximum number of trees that will be displayed at any one time.
PARAMETER 2 = 0; No longer used but has been left so that older scenario files

Figure A-5: Tree type: #1 and #8

will be compatible.

PARAMETER 3 = *1$\tilde{1}$8;-4;-15; Types of tree that will be display. Randomly chosen from tree types from 1 to 18 excluding 4 and 15, which are palm trees. For example, tree type 1 and 8 are shown in Fig. A-5.

PARAMETER 4 = 25; Minimum lateral position from the specified position to the trees, in m.

PARAMETER 5 = 30; Maximum lateral position from the specified position to the trees, in m.

PARAMETER 6 = 0; The trees will appear on both side of the road.

V = Vehicle ahead of driver in driver's lane

PARAMETER 1 = 27; The speed, in m/s, of the new vehicle.

PARAMETER 2 = 100; The longitudinal distance, in m, that the vehicle is away from the driver when the vehicle initially appears.

PARAMETER 3 = 05; The vehicle's initial lateral position, in m.

PARAMETER 4 = 1; Brake lights become brighter when the vehicle begins braking.

PARAMETER 5 = 2; Vehicle model type number. Fig. A-4 shows the model used for the V event in the experiment.

PARAMETER 6 = 57289{15}; The absolute longitudinal distance down the road where the object is currently positioned as the trigger.

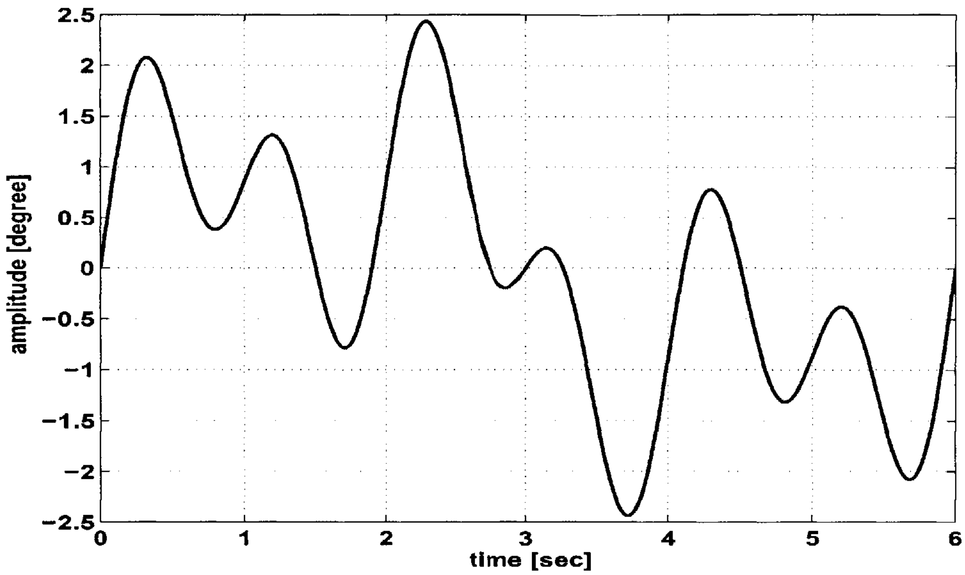

Figure A-6: One period of pseudo-random disturbances for WG

PARAMETER 7 = 0; Lateral position specification specifying how the vehicle will move laterally.

PARAMETER 8 = 0; New speed, in m/s, that the vehicle will traveling at the end of the transition period.

PARAMETER 9 = 2; The amount of time, in m/s, that the transition will occur over.

WG = Wind gusts

PARAMETER 1 = 1; Steering wheel gain, in radians.

PARAMETER 2 = 0; Throttle controller gain.

PARAMETER 3 = 4; Run length multiplier;

PARAMETER 4 = blank; The default WINDGUST.PAR file is used. The file specifies that 3 separate sine waves that will be summed together into 1 final wave. The total length of the final wave will be 6 seconds. Each of the 3 sine waves specified has an amplitude of 1 and their periods vary from 6 to 1. The sine wave with a period of 6 will have 6 maximum peaks occur during the 6 second wave, the wave with a period 3 will have 3 maximum peaks occur, and the wave with 1 period will have a single maximum peak. Fig. A-6 shows the superposed sine wave used in the WG.

Table A.1: Simulated Tasks

Simulated Tasks	STISIM event
CL (Curved Lane Tracking)	C
CS (Straight Lane Tracking given Changes of Steering Dynamics)	OM
LV (Straight Lane Tracking given a Lead Vehicle)	FLLW
LT (Straight Lane Tracking)	ROAD
WG (Straight Lane Tracking given Wind Gusts)	WG
SLCT (Single Lane Change Task)	SOBJ
DLCT (Double Lane Change Task)	SOBJ
APVT (Auditory Psychomotor Vigilance Task)	PR
VPVT (Visual Psychomotor Vigilance Task)	DA
EM (Emergency Maneuver)	V

Table A.1 summarizes the simulated tasks and the corresponding STISIM events which enabled us to program the tasks. We used Previously Defined Event (PDE) file to model each task. PDE allows us to group a set of events into a single file.

A.2 Forms used in Experiment

Fig. A-7 and Fig. A-8 are Pre-Experiment Questionnaire given to all the subjects. Fig. A-9 and Fig. A-10 are sleep diaries for non-sleep-deprived and partially sleep-deprived conditions respectively. All subjects are required to write down their bed time and get up time days before the experiment. Fig. A-11 is a participant informed consent form which all the subjects are required to read it before the experiment stats. They are required to sign the form if they decided to participate in the experiment. A copy of the signed form (both signatures from the participant and a witness) is given to the participant.

A.3 Participant Data

Table A.2 summarizes data from all participants.

First column: Subject Number

Second column: Gender. M = male and F = female.

Third column: Age

Table A.2: Participant data

Subj. Numb.	Gender	Age	Normal sleep	Ideal sleep	Snoring	Sleep prob.	Drowsy driving
S01	M	31	7.0	9.0	2.0	1.0	1.0
S02	M	46	6.0	8.0	2.0	2.0	1.0
S03	M	38	8.0	7.5	3.0	2.0	2.0
S04	M	45	7.0	8.0	3.0	2.0	2.0
S05	M	40	5.0	6.0	4.0	3.0	1.0
S06	M	48	7.0	8.0	1.0	1.0	2.0
S07	M	46	6.0	7.0	5.0	3.0	1.0
S08	M	43	7.0	8.0	5.0	1.0	3.0
S09	M	45	7.0	9.0	5.0	4.0	4.0
S10	M	49	7.0	8.0	3.0	1.0	3.0
S11	M	29	7.0	8.0	4.0	1.0	1.0
S12	M	40	6.0	8.0	2.0	4.0	3.0
Avg.	N/A	41.7	6.7 hours	7.9 hours	3.3	2.1	2.0
Std.	N/A	6.4	46.7 min	48.1 min	1.4	1.2	1.0

Fourth column: The estimated number of hours of sleep each subject had per day during past 2 weeks

Fifth column: Ideal amount of sleep per day the subject feel

Sixth column: Snoring score (1 = Not at all, 3 = Sometimes, and 5 = Excessively)

Seventh column: Influence of sleep problems to work or family life (1 = Not at all, 3 = Sometimes, and 5 = Excessively)

Eight column: Frequency of dozing off while driving (1 = Not at all, 3 = Sometimes, and 5 = Excessively)

A.4 Miscellaneous

Fig. A-12 is a start-up image of STISIM driving simulator for the experiment. Fig. A-13 shows a dimension of the driver's seat.

Ford/MIT alliance project: Detection of human drowsiness in simulated driving
Pre-Experiment questionnaire

I. Please circle one.

1. Estimate the average number of hours of sleep you had per day during the last 2 weeks.

Less then 3	4	5	6	7	8	9	More then 10

2. What do you feel is your ideal amount of sleep per day?

Less then 3	4	5	6	7	8	9	More then 10

II. Please circle one based on the following scale.

1	2	3	4	5
No Not at all.		Neutral Sometimes		Yes. Excessively

3. Have you been told you snore?

1	2	3	4	5

4. Is your work or family life affected by sleep problems?

1	2	3	4	5

5. Do you find yourself dozing while driving?

1	2	3	4	5

Figure A-7: Pre-Experiment Questionnaire - page 1 of 2

III. Please answer the following questions.

6. Do you have any sleep disorders?

____

7. Do you have any other health problems?

____

8. Are you on any medication?

____

Figure A-8: Pre-Experiment Questionnaire - page 2 of 2

Sleep diary

Name:

Day	Date	Bed time	Get up time	Comments
1	July , 06			
2	July , 06			
3	July , 06			
4	July , 06			
5	July , 06			
6	July , 06			
7	July , 06			

Time-in-bed should be **MORE THAN 8** hours for everyday.

<<Example>>

Day	Date	Bed time	Get up time	Comments
1	March 4, 2006 Saturday	11:20 pm	7:30 am	I felt still fatigued when I woke up.
2	March 5, 2006 Sunday	11:00 pm	6:15 am	I had a really good sleep.

Figure A-9: Sleep-diary for non-sleep-deprived subjects

Sleep diary

Name:

Day	Date	Bed time	Get up time	Comments
1	June , 06			
2	June , 06			
3	June , 06			
4	June , 06			
5	June , 06			
6	June , 06			
7	June , 06			

Day : Time-in-bed should be **LESS THAN 7** hours.

Day : Time-in-bed should be **LESS THAN 4** hours.

You are not allowed to take a nap! Sorry. ☺
Do not consume any alcohol- or caffeine- containing beverage e.g., beer, wine, tea or coffee on the day of your sleep study.

<<Example>>

Day	Date	Bed time	Get up time	Comments
1	March 4, 2006 Saturday	11:20 pm	7:30 am	I felt still fatigued when I woke up.
2	March 5, 2006 Sunday	11:00 pm	6:15 am	I had a really good sleep.

Figure A-10: Sleep-diary for partially sleep-deprived subjects

Detection of Human Drowsiness in Simulated Driving
Ford/MIT Alliance Project

PARTICIPANT INFORMED CONSENT

Purpose of this Research: The purpose of this study is to improve safety in driving via the detection and countermeasure of human drowsiness.

Study Procedure: This study will take place at 3A029, Building 5 where a driving simulator is located. While driving the simulator, some people experience motion sickness. If you feel uncomfortable at any time, tell the experimenters immediately. You can stop the experiment at any time. If you volunteer to participate in this study, we would ask you to do the following things:

- Make sure that you are not subjected to serious medication that may prevent you from driving continuously for 2 hours on our simulator.
- Make sure that you do not drink any alcohol-or caffeine-containing beverage, e.g., beer, wine, tea, or coffee, within 6 hours prior to the test.
- Attend a warm-up session: The investigator will explain how to operate the steering wheel and brake /throttle pedal. Practice on the program until an adequate level of performance is achieved, which means that you feel comfortable operating the system.
- The main simulated driving session will last about 100 minutes.

We will be collecting data including steering and brake/throttle control inputs and will be recording (using video device) your driving behavior.

Potential Risks: There are no anticipated risks.

Potential Benefits: While there is no foreseeable benefit to you as a participant in this study, your efforts will help us design methods to detect drowsiness of drivers and thus to promote safe driving for people in general.

Confidentiality of Data – Participant Identity: The data gathered in this experiment is the property of Ford/MIT alliance and will be kept confidential. Each participant's name will be separated from their data. A coding scheme will be used to identify each participant's data by gender and number only (e.g., Male, Participant No. 3). Video clips (or still images) of your test session may be used in Ford/MIT presentations and may be released to the press. Your name will not be mentioned.

Freedom to Withdraw: The study should take approximately 2 hours to complete. If you have any procedural questions about the study, please do not hesitate to ask the experimenter at any time. You are free to withdraw from the study at any time without question.

Participant's Permission: I have read and understand the informed consent and conditions of this study. I am not subject to serious medication that prevents me from 2 hour simulated driving and do not believe there is any reason why I should not participate in this study. I have been advised that if I have any doubts about my desires to participate in the study, I should not do so.

____________________________ ____________________________

Name (PRINTED) Date

____________________________ ____________________________

Signature Witness (Experimenter)

Figure A-11: Participant Informed Consent Form

Figure A-12: Startup image of experiment

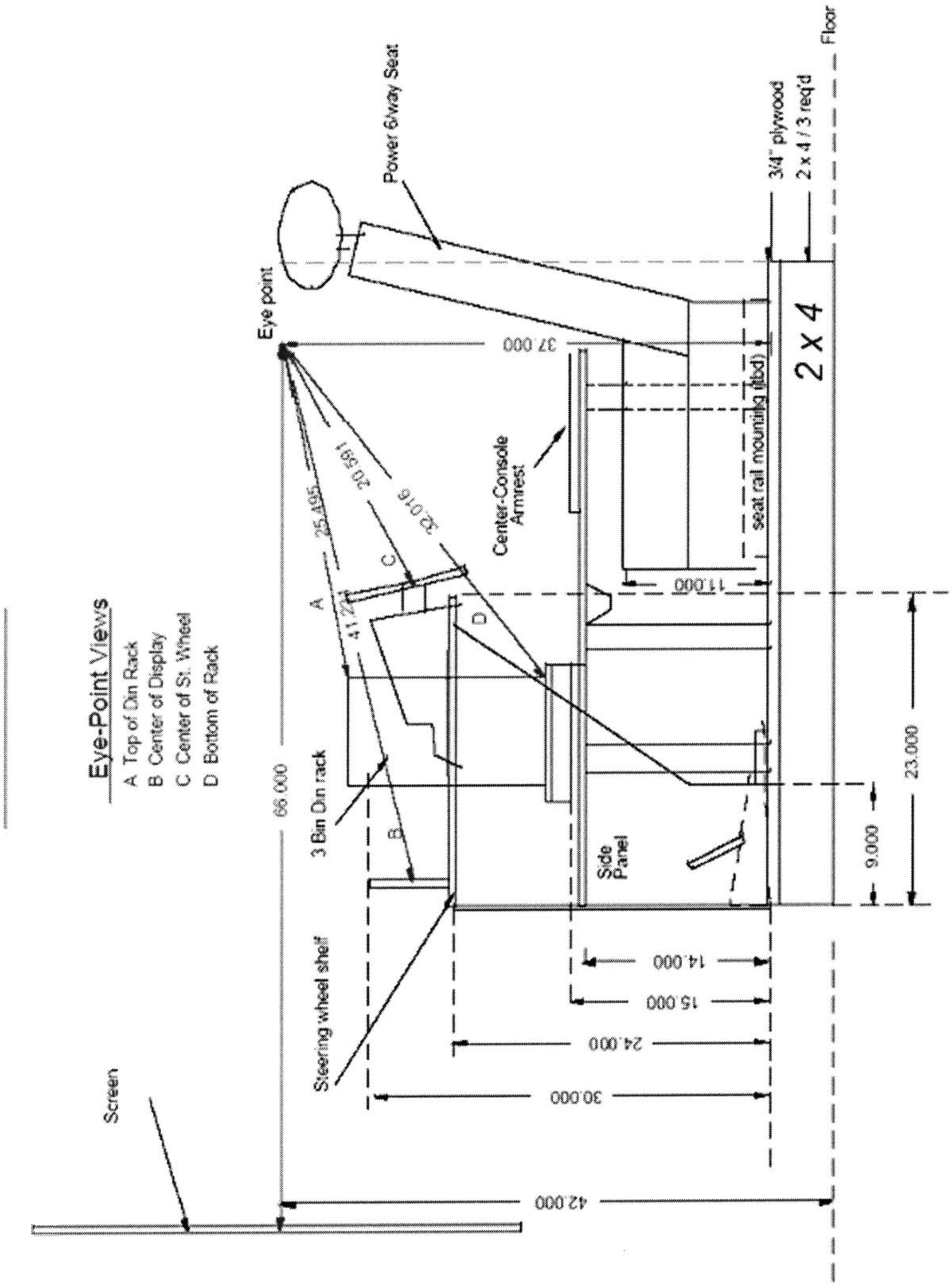

Figure A-13: Seat Buck Design [6]

Appendix B

Supplementary Experimental Results

B.1 Estimated Parameters in the Crossover Model

Table B.1 and B.2 provide the estimated parameters in the Crossover Model for each subject.

Table B.1: The Crossover Model: gain K

Tasks	SLCT		DLCT	
Sleep-Depr. level	Non-Sleep-Depr.	Partial-Sleep-Depr.	Non-Sleep-Depr.	Partial-Sleep-Depr.
Subject	Gain			
1	0.9497	0.6605	1.1739	0.5591
2	0.3543	0.3310	0.2710	0.2523
3	0.4209	0.3711	0.3592	0.3733
4	0.4753	0.3463	0.2761	0.3301
5	0.5950	0.7483	0.4438	0.6266
6	0.6021	0.5010	0.4113	0.3328
7	0.6129	0.3084	0.5201	0.8049
8	0.7915	0.5626	0.5108	0.1205
9	-0.3620	0.7371	0.5820	1.3599
10	0.4085	0.2134	0.4001	0.2408
11	0.7224	0.5643	0.5994	0.4390
12	0.6425	0.6870	0.4587	0.5379
mean	0.5178	0.5026	0.5005	0.4981
STD	0.3254	0.1845	0.2367	0.3306
p-value	0.5543		0.5095	

Table B.2: The Crossover Model: effective time delay τ

Tasks	SLCT		DLCT	
Sleep-Depr. level	Non-Sleep-Depr.	Partial-Sleep-Depr.	Non-Sleep-Depr.	Partial-Sleep-Depr.
Subject	Effective Time Delay [sec]			
1	1.14	0.93	1.19	1.07
2	1.46	1.99	1.65	2.07
3	1.25	1.19	1.30	1.37
4	1.39	1.88	2.02	1.66
5	1.05	0.81	0.82	0.87
6	0.80	1.13	0.98	1.56
7	0.91	1.13	0.98	1.56
8	1.28	1.42	0.93	1.11
9	0.93	1.11	1.24	1.28
10	1.00	0.73	1.10	1.63
11	0.82	0.86	0.90	0.90
12	1.03	0.93	0.93	1.05
mean	1.0833	1.1749	1.1675	1.3190
STD	0.2173	0.4015	0.3565	0.3571
p-value	0.1484		**0.0408**	

B.2 Individual SOC curves

Fig. B-1 to Fig. B-12 represent SOC curves obtained from stimulus-response task performance.

B.3 Definition of d-separation

When the state of a variable is known we say that it is *instantiated.* [53, 59]

Serial connections Fig. B-13 shows that A is a parent node of B, B is a parent node of C. If B is uninstantiated then, evidence about A influence the certainty of B, which then influences the certainty of C (Forward serial connection). Similarly, evidence about C flows through B to A (Backward serial connection). If B is instantiated, then the evidence does not propagate through from A to C or from C to A; A and C become independent.

Diverging connections Consider the situation in Fig. B-14 ; A has children $B, C, \cdots, E$. Evidence transmit thorough A unless it is instantiated.

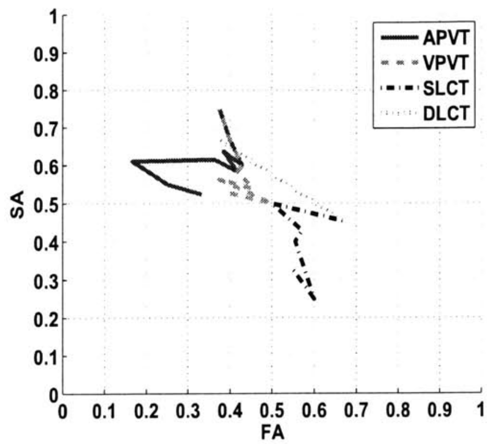

Figure B-1: SOC curve: Subject #1

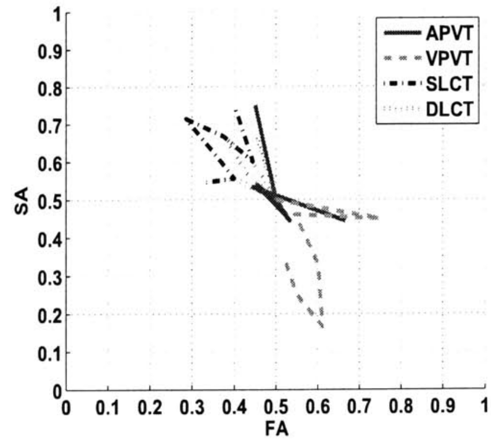

Figure B-2: SOC curve: Subject #2

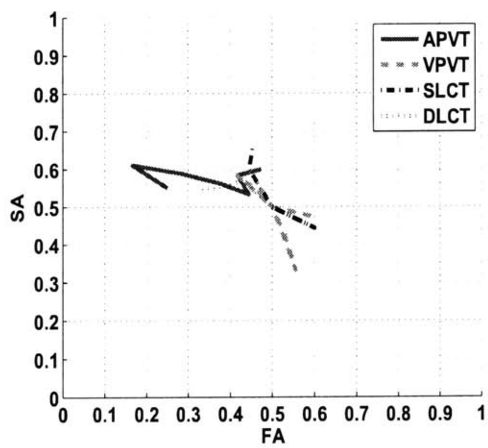

Figure B-3: SOC curve: Subject #3

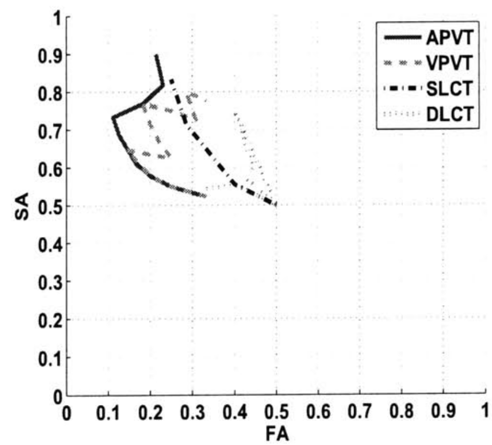

Figure B-4: SOC curve: Subject #4

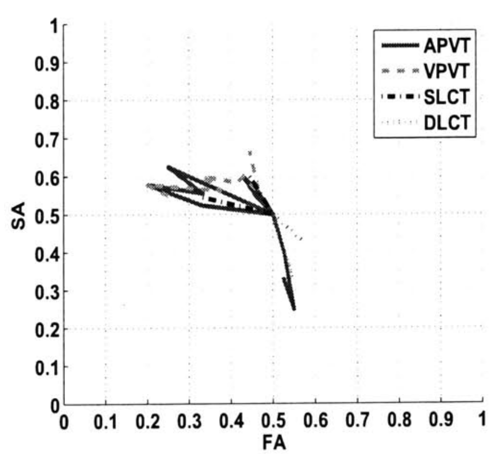

Figure B-5: SOC curve: Subject #5

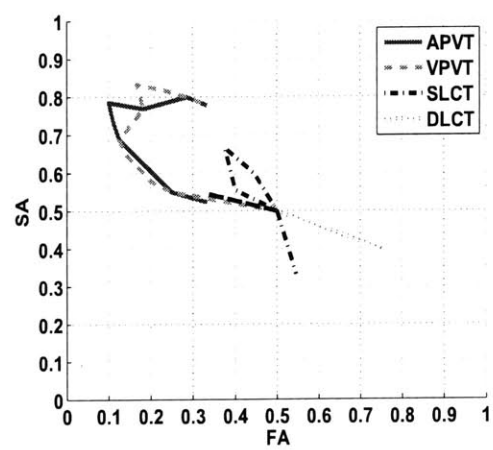

Figure B-6: SOC curve: Subject #6

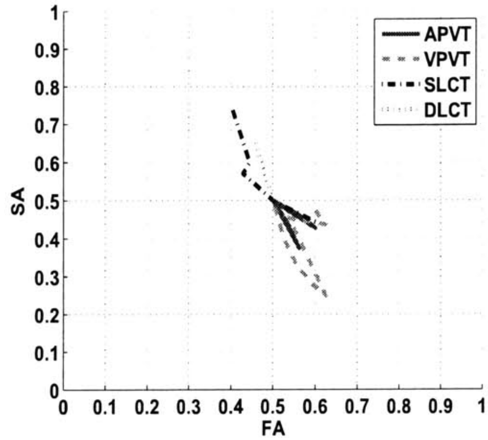

Figure B-7: SOC curve: Subject #7

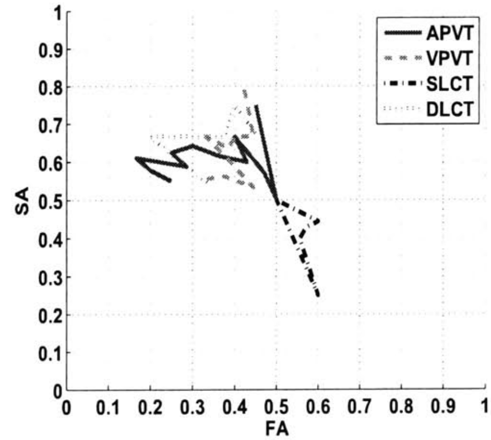

Figure B-8: SOC curve: Subject #8

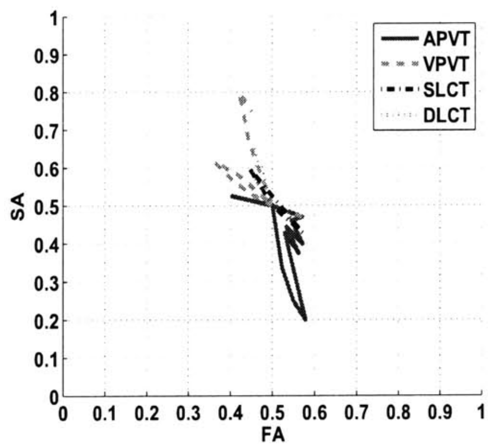

Figure B-9: SOC curve: Subject #9

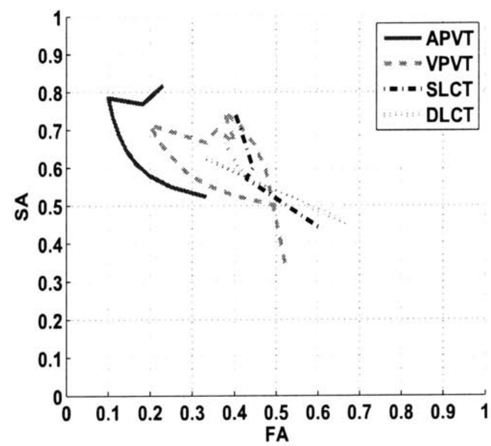

Figure B-10: SOC curve: Subject #10

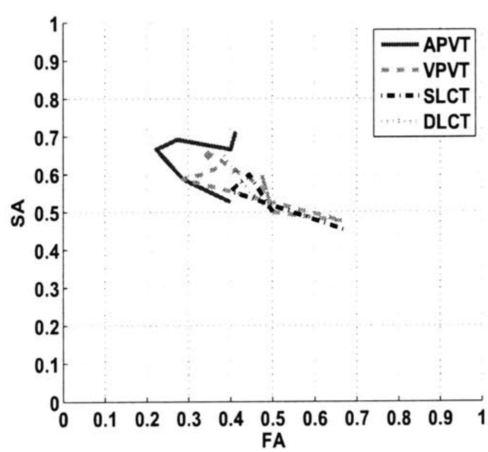

Figure B-11: SOC curve: Subject #11

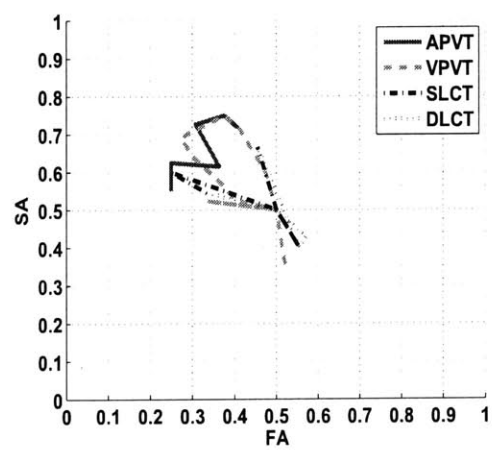

Figure B-12: SOC curve: Subject #12

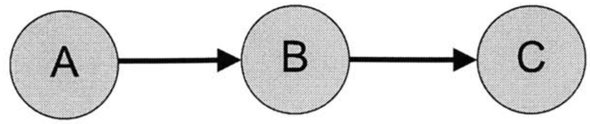

Figure B-13: Serial connection. [53]

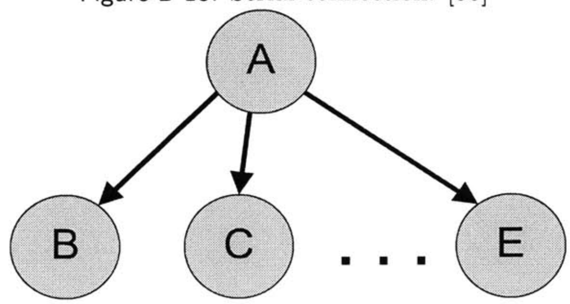

Figure B-14: Diverging connection. [53]

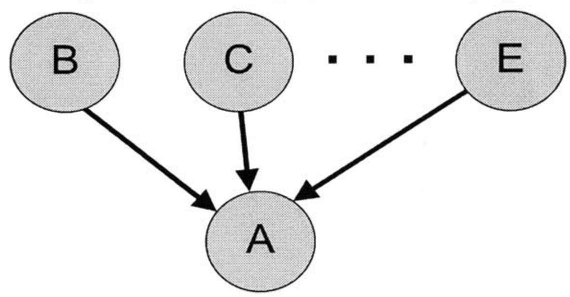

Figure B-15: Converging connection. [53]

Converging connections The situation in Fig. B-15 is converging connection, A has parents $B, C, \cdots, E$. Evidences transmit between $B, C, \cdots, E$ only if A or descendant of A is initiated. If we see evidence for A, then $B, C, \cdots, E$ become dependent. This explains *explaining away* effect; if we find A has occurred and then get information that C has occurred, the certainty of B will decrease.

Definition Two distinct variables A and B in a causal network are $d-separated$ if, for all parts between A and B, there is an intermediate variable V (distinct from A and B) such that either

- The connection is serial or diverging and V is instantiated
- The connection is converging, neither V nor any of V's descendants have received evidence.

Bibliography

[1] Aboukhalil, A. "Systems Approach to the Design of Locomotive Fatigue Management Technologies". Master's thesis, Massachusetts Institute of Technology, 2006.

[2] Achermann, P. "The Two-Process Model of Sleep Regulation Revisited". *Aviation, Space, and Environmental Medicine, Vol. 75*, No. 3 (2004), pp. A37–A43.

[3] Åkerstedt, T., Folkard, S., and Portin, C. "Predictions from the Three-Process Model of Alertness". *Aviation, Space, and Environmental Medicine, Vol. 75*, No. 3 (2004), pp. A75–A83.

[4] Åkerstedt, T., and Gillberg, M. "Subjective and objective sleepiness in the active individual". *International Journal of Neuroscience, Vol. 52* (1990), pp. 29–37.

[5] Allahyar, M. *Wakefulness, Alertness, Sleep, and Dreams*, 1997. www.csun.edu/~vcpsy00h/students/sleep.htm.

[6] Angell, L., Auflick, J., Austria, P., Kochhar, D., Tijerian, L., Biever, W., Diptiman, T., Hogsett, J., and Kiger, S. "Driver Workload Metrics Task 2 Final Report". Tech. Rep. DOT HS 810 635, 2006.

[7] Arnedt, J., Wilde, G., Munt, P., and MacLean, A. "Simulated driving performance following prolonged wakefulness and alcohol consumption: separated and combined contributions to impairment". *Journal of Sleep Research, Vol. 9*, No. 3 (September 2000), pp. 233–241.

[8] AYOOB, E. M., GRACE, R., AND STEINFIELD, A. "A User-Centered Drowsy Driver Detection and Warning System". Tech. Rep. 1-58113-728-1, Association for Computer Machinery, 2003.

[9] AYOOB, E. M., STEINFIELD, A., AND GRACE, R. "Identification of an "appropriate" drowsy driver detection interface for commercial vehicle operations". In *Proceedings of Human Factors and Ergonomics Society 47th Annual Meeting* (2003), pp. 1840–1844.

[10] BANKS, S., CATCHESIDE, P., LCAK, L., GRUNSTEIN, R., AND MCEVOY, D. "The Maintenance of Wakefulness Test and Driving Simulator Performance". *Sleep, Vol. 28* (2005), pp. 1381–1385.

[11] BEAR, M., CONNORS, B., AND PARADISO, M. *Neuroscience: Exploring the Brain*, 2nd edition ed. Lippincott Williams & Wilkins, 2001.

[12] BELZ, S. *An On-Road Investigation of Self-Rating of Alertness and Temporal Separation as Indicators of Driver Fatigue in Commercial Motor Vehicle Operators.* PhD thesis, Virginia Polytechnic Institute, 2000.

[13] BILLIARD, M. *Sleep: Physiology, Investigations, and Medicine.* Springer, 2003.

[14] BLATTER, K., GRAW, P., MÜNCH, M., KNOBLAUCH, V., WIRZ-JUSTICE, A., AND CAJOCHEN, C. "Gender and age differences in psychomotor vigilance performance under differential sleep pressure conditions". *Behavioral Brain Research* (2006), pp. 312–317.

[15] BRENNAN, S., AND ALLEYNE, A. "A Statistical Survey of Vehicle Model Parameter Distributions". Tech. rep., Dept. of Mechanical & Industrial Engineering, University of Illinois at Urbana-Champaign.

[16] BRILL, J., MOULOUA, M., HANCOCK, P., GILSON, R., AND KENNEDY, R. "Assessing spare attentional capacity of drowsy drivers: Protocol development". In *2nd International Symposium of Human Factors in Driver Assessment* (2003).

[17] BROOKS, V. *The neural basis of motor control.* Oxford University Press, 1986.

[18] BROWN, I. D. "PROSPECTS FOR TECHNOLOGICAL COUNTERMEASURES AGAINST DRIVER FATIGUE". *Accident Analysis and Prevention, Vol. 29* (1997), pp. 525–531.

[19] BUCKNER, D., AND MCGRATH, J., Eds. *Vigilance: A Symposium.* McGraw-Hill Book Company, 1963.

[20] CALHOUN, V., PEKAR, J., MCGINTY, V., ADALI, T., WATSON, T., AND PEARLSON, G. "Different Activation Dynamics in Multiple Neural Systems During Simulated Driving". *Human Brain Mapping, Vol. 16* (2002), pp. 158–167.

[21] CANADA SAFETY COUNCIL. "Safety Canada: Drivers on Pot - Issues and Options". Tech. Rep. Vol. XLVII No. 4, 2003.

[22] CARLSON, N. *Physiology of Behavior*, 6th edition ed. Allyn and Bacon, 1998.

[23] CARROLL, R. "Eye-Activity Measures of Fatigue and Napping as a Fatigue Countermeasure". Tech. Rep. FHWA-MCRT-99-010, FHWA, Office of Motor Carrier and Highway Safety, April 1999.

[24] CHEN, L.-K., AND ULSOY, A. G. "Identification of a Driver Steering Model, and Model Uncertainty, From Driving Simulator Data". *Transactions of the ASME:Journal of Dynamics Systems, Measurements, and Control, Vol. 123* (December 2001), pp. 623–629.

[25] COHEN, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd edition ed. L. Erlbaum Associates, 1988.

[26] COUGHLIN, J., AND REIMER, B. "New Demands from and Older Population: An Integrated Approach to Defining the Future of Older Driver Safety". In *Convergence Transportation Electronics Association and SAE International* (2006).

[27] DANIEL, R. "Alpha and Theta EEG in Vigilance". *Perceptual and Motor Skills, Vol. 25* (1967), pp. 697–703.

[28] DEMENT, W. *The Sleep Well*, 2000. www.stanford.edu/~dement.

[29] DIJK, D.-J., AND CZEISLER, C. "Contribution of the Circadian Pacemaker and the Sleep Homeostat to Sleep Propensity, Sleep Structure, Elcetroencephalographic Slow Waves, and Sleep Spindle Activity in Humans". *The Journal of Neuroscience, Vol. 15* (1995), pp. 3526–3538.

[30] DINGES, D. "An overview of sleepiness and accidents". *Journal of Sleep Research., Vol. 4* (1995), pp. 4–14.

[31] DINGES, D. "The Promise and Challenges of Technologies for Monitoring Operator Vigilance". In *Proceedings of the International Conference on Managing Fatigue in Transportation, American Trucking Associations Foundation* (Tampa, FL, 1997), pp. 77–86.

[32] DINGES, D., AND KRIBBS, N. "Performing While Sleepy: Effects of Experimentally-Induced Sleepiness". In *Sleep, Sleepiness, and Performance* (1991), John Wiley & Sons Ltd., pp. 97–128.

[33] DINGES, D., MALLIS, M., MAISLIN, G., AND POWELL, J. "Final Report: Evaluation of Techniques for Ocular Measurement as an Index of Fatigue and the Basis for Alertness Management". Tech. Rep. DOT HS 808 762, NHTSA, 1998.

[34] DINGES, D., PACK, F., WILLIAMS, K., GILLEN, K., POWELL, J., OTT, G., APTOWICZ, C., AND PACK, A. "Cumulative Sleepiness, Mood Disturbance, and Psychomotor Vigilance Performance Decrements During a Week of Sleep Restricted to 4-5 Hours per Night". *Sleep, Vol. 20*.

[35] DINGUS, T., HULSE, M., JAHNS, S., ALVES-FOSS, J., CONFER, S., RICE, A., ROBERTS, I., HANOWSKI, R., AND SORENSON, D. "Development of Human Factors Guidelines for Advanced Traveler Information Systems and Com-

mercial Vehicle Operations: Literature Review". Tech. Rep. FHWA-RD-95-153, Federal Highway Administration, 1996.

[36] DRAKE, C. 2006. Private communication, Henry Ford Hospital.

[37] EVANS, L. *Traffic Safety.* Science Serving Society, Bloomfield Hills, MI, 2004.

[38] FEDERAL MOTOR CARRIER SAFETY ADMINISTRATION. "Commercial Motor Vehicle/Driver Fatigue and Alertness Study". Tech. rep., 1996.

[39] FORD MOTOR COMPANY. 2005. media.ford.com.

[40] FRANKEN, R. *Human Motivation*, 3rd edition ed. Brooks/Cole Publishing Company, 1994.

[41] FUENTES, C. "Fatal Motor Vehicle Accident: Comparative Data Report for the State of New Jersey". Tech. rep., New Jersey State Police Fatal Accident Investigation Unit, 2005.

[42] GRACE, R. "Drowsy Driver Monitor and Warning System". Tech. rep., Carnegie Mellon University, 2001.

[43] GRACE, R., BYRNE, V. E., BIERMAN, D., LEGRAND, J.-M., GRICOURT, D., DAVIS, R., STAZEWSKI, J., AND CARNAHAN, B. "A Drowsy Driver Detection System for Heavy Vehicles". Tech. Rep. 0-7803-5086-3, IEEE, 1998.

[44] GREENBERG, J. 2006. Private communication, Ford Motor Company.

[45] GROEGER, J. *Understanding Driving: Applying cognitive psychology to a complex everyday task.* Pshycology Press, Talyor & Francis Group, 2000.

[46] HADDON, W. "A logical framework for categorizing highway safety phenomena and activity". *Journal of Trauma, Vol. 12* (1972), pp. 193–207.

[47] HARTLEY, L., Ed. *Managing Fatigue in Transportation*, first edition ed. Elsevier Science Ltd., 1998.

[48] HOBSON, A. *Sleep.* Scientific American Library, 1989.

[49] HOLZBECHER, J., HOLZMANN, F., BELLINO, M., SULZMAN, A., JACOT, J., AND RYSER, P. "Driver Alertness Sensing". In *Proceedings of the IEEE Intelligent Transportation Systems Conference* (2006).

[50] HORNE, J. *Why we sleep.* Oxford University Press, 1988.

[51] HORVITZ, E. *Display of Information for Time-Critical Decision Making*, 1995. research.microsoft.com/~horvitz/vista.htm.

[52] HUNGS, M., AND MIGNOT, E. "Hypocretin/orexin, sleep and narcolepsy". *BioEssays, Vol. 3* (2001), pp. 397–408.

[53] JENSEN, F. *Bayesian Networks and Decision Graphs.* Springer, 2001.

[54] JI, Q., LAN, P., AND LOONEY, C. "A Probabilistic Framework for Modeling and Real-Time Monitoring Human Fatigue".

[55] JOHNS, M. "Sensitivity and specificity of the multiple sleep latency test (MSLT), the maintenance of wakefulness test and the Epworth sleepiness scale: Failure of the MSLT as a gold standard". *Journal of Sleep Research* (2000), pp. 5–11.

[56] JOHNSON, E., AND PRITCHETT, A. "Generic Pilot and Flight Control Model for Use in Simulation Studies". In *AIAA Modeling and Simulation Technologies Conference and Exhibit* (Monterey, CA, August 5-8 2002). AIAA 2002-4694.

[57] JORDAN, M., Ed. *Learning in Graphical Models.* MIT Press, 1998.

[58] JUEPTNER, M., AND WEILLER, C. "A review of differences between basal ganglia and cerebellar control of movements as revealed by functional imaging studies". *Brain, Vol. 121* (1998), pp. 1437–1449.

[59] KAELBLING, L. *Techniques in Artificial Intelligence*, 2002. MIT OpenCourse-Ware.

[60] KANDEL, E., SCHWARTZ, J., AND JESSELL, T. *Principles of Neural Science.* McGraw-Hill Book Company, 2000.

[61] KANEDA, M., IIZUKA, H., UENO, H., HIRAMATSU, M., TAGUCHI, M., AND TSUKINO, M. "Development of a Drowsiness Warning System". In *The Fourteenth International Technical Conference on Enhanced Safety of Vehicles* (Munich, Germany, 1994), no. 94-S3-O-08.

[62] KHOURY, J. *Simulation of a crash prevention technology at a no-passing zone site.* PhD thesis, Virginia Polytechnic Institute, 2003.

[63] KIRCHER, A. "Vehicle Control and Drowsiness". Tech. Rep. VTI Meddelande 922A, Swedish National Road and Transport Research Institute, 2002.

[64] KLAUER, S., DINGUS, T., NEALE, V., SUDWEEKS, J., AND RAMSEY, D. "The Impact of Driver Inattention on Near-Crash/Crash Risk: An Analysis Using the 100-Car Naturalistic Driving Study Data". Tech. Rep. DOT HS 810 594, NHTSA and Virginia Tech Transportation Institute, 2006.

[65] KLEITMAN, N. *Sleep and Wakefulness.* The University of Chicago Press, 1963.

[66] KLYDE, D., MCRUER, D., AND MYERS, T. "Pilot-Induced Oscillation Analysis and Prediction with Actuator Rate Limiting". *AIAA Journal of Guidance, Control and Dynamics, Vol. 20* (1997), pp. 81–89.

[67] KNIPLING, R. "PERCLOS: A Valid Psychophysiological Measure of Alertness as Assessed by Psychomoter Vigilance". Tech. Rep. HWA-MCRT-98-006, FHWA, Office of Motor Carrier and Highway Safety, October 1999.

[68] KOREA BROADCASTING SYSTEM NEWS. *Pile-Up Crash Occurred on Kyungbu-Highway*, 2007. news.kbs.co.kr/exec/news/news.php?id=1283245 & kind=c.

[69] KOZAK, K., CURRY, R., GREENBERG, J., ARTS, B., BLOMMER, M., AND CATHEY, L. "Leading indicators of drowsiness in simulated driving". In *Human Factors and Ergonomics Society 49th Annual Meeting* (Orlando, FL, September 26-30 2005).

[70] KUCHAR, J. K. *A Unified Methodology for the Evaluation of Hazard Alerting Systems.* PhD thesis, Department of Aeronautics and Astronautics, MIT, 1995.

[71] KUTNER, M. *Applied linear statistical models.* McGraw-Hill, 2005.

[72] KUTNER, M., NETER, J., NACHTSHEIM, C., AND LI, W. *Applied Linear Statistical Models.* The McGraw-Hill College, 2004.

[73] LAL, S., AND CRAIG, A. "A critical review of the psychophysiology of driver fatigue". *Biological Psychology, Vol. 55* (2000), pp. 173–194.

[74] LENNE, M., REGAN, M., TRIGGS, T., AND HAWORTH, N. "A preliminary Examination of Railroad Dispatcher Workload, Stress, and Fatigue". Tech. Rep. PR02-02, U.S. Department of Transportation, Federal Railroad Administration, 2002.

[75] LENNE, M., REGAN, M., TRIGGS, T., AND HAWORTH, N. "Review of recent research in applied experimental psychology: Implications for countermeasure development in road safety". Tech. Rep. 0 7326 1733 2, Monash University Accident Research Centre, 2004.

[76] LIU, Z., DING, L., AND HE, B. "Integration of EEG/MEG with MRI and fMRI". *IEEE Engineering in Medicine and Biology Magazine*, pp. 46–53.

[77] LONGHURST, G. "Understanding Driver Visual Behaviour". Tech. rep., Seeing Machines, 2001.

[78] LYNCH, D. P. "Velocity Scheduled Driver Assisted Control of a Four-Wheel Steer Vehicle". Master's thesis, University of Illinois at Urbana-Champaign, 2000.

[79] MACKIE, R. R., AND WYLIE, C. D. "Countermeasures to Loss of Alertness in Motor Vehicle Drivers: A Taxonomy and Evaluation". In *Proceedings of the Human Factors Society 35th Annual Meeting* (1991).

[80] MALLIS, M., MAISLIN, G., KONOWAL, N., BYRNE, V., BIERMAN, D., DAVIS, R., GRACE, R., AND DINGES, D. "Biobehavioral Responses to Drowsy Driving Alarms and Alerting Stimuli". Tech. Rep. DTNH22-93-D-07007, Carnegie Mellon Research Institute and NHTSA, 1999.

[81] MARBERGER, C., DANGELMAIER, M., WIDLROITHER, H., AND BEKIARIS, E. "User centered HMI development in the AWAKE-project". In *23rd European Annual Conference on Human Decision Making and Manual Control* (The Hague, Netherlands, October 11 2004). 0-7803-8566-7/04.

[82] MCRUER, D., AND WEIR, D. H. "Theory of Manual Vehicular Control". *Ergonomics, Vol. 12*, No. 4 (1969), pp. 599–633.

[83] MCRUER, D. T. *Mathematical models of human pilot behavior.* North Atlantic Treaty Organization, Advisory Group for Aerospace Research and Development, 1974.

[84] MCRUER, D. T., CLEMENT, W. F., THOMPSON, P. M., AND MAGDALENO, R. E. "Minimum Flying Qualities Volume II: Pilot Modeling for Flying Qualities Applications". Tech. Rep. No. 1235-1, Wright Research & Development Center, Systems Technology, Inc., 1989.

[85] MENA-SEGOVIA, J., BOLAM, J. P., AND MAGILL, P. "Pedunculopontine nucleus and basal ganglia: distant relatives or part of the same family?". *TRENDS in Neurosciences, Vol. 27*, No. 10 (2004), pp. 585–588.

[86] MEYER, J., AND COUGHLIN, J. "Order drivers and new in-vehicle devices.". *Public Policy and Aging Bulletin, Vol. 11*.

[87] MIGNOT, E., TAHERI, S., AND NISHINO, S. "Sleeping with the hypothalamus: Emerging therapeutic targets for sleep disorders". *Nature Neuroscience Supplement, Vol. 5* (2002), pp. 1071–1075.

[88] MINIMITTER. *Actiwatch manual*, 2005.

[89] MODJTAHEDZADEH, A., AND HESS, R. A. "A Model of Driver Steering Control Behavior for Use in Assessing Vehicle Handling Qualities". *Transactions of the ASME, Vol. 115* (September 1993), pp. 456–464.

[90] MURPHY, K. *A Brief Introduction to Graphical Models and Bayesian Networks*, 1998. www.cs.ubc.ca/~murphyk/Bayes/bnintro.html.

[91] MURPHY, K. "An introduction to graphical models". Tech. rep., 2001. www.cs.ubc.ca/~murphyk/Papers/intro_gm.pdf.

[92] NATIONAL AERONAUTICS AND SPACE ADMINISTRATION, AND NATIONAL TRANSPORTATION SAFETY BOARD. *Fatigue Resource Directory*, 1995. human-factors.arc.nasa.gov/zteam/fredi/home-page.html.

[93] NATIONAL SLEEP FOUNDATION. "Sleep-Wake Cycle: Its Physiology and Impact on Health". Tech. rep., 2006.

[94] NATIONAL SLEEP FOUNDATION. 2007. www.sleepfoundation.org.

[95] NATIONAL TRANSPORTATION SAFETY BOARD. "Evaluation of U.S. Department of Transportation Efforts in th 1990s to Address Operator Fatigue". Tech. Rep. NTSB/SR-99/01 PB99-917002, 1999.

[96] NEALE, V., DINGUS, T., KLAUER, S., SUDWEEKS, J., AND GOODMAN, M. "An overview of the 100-car naturalistic study and findings". Tech. Rep. 05-0400, Virginia Tech Transportation Institute and National Highway traffic Safety Administration, 2005.

[97] NIEDERMEYER, E. "Sleep and EEG". In *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields* (Lippincott Williams & Wilkins, 2004), pp. 174–188.

[98] PHILIP, P., SAGASPE, P., TAILLARD, J., VALTAT, C., MOORE, N., ÅKERSTEDT, T., CHARLES, A., AND BIOULAC, B. "Fatigue, sleepiness and performance in simulated versus real driving conditions". Tech. rep. supported by a grant from Direction Générale des Armées.

[99] PILUTTI, T. "Application: Driver Status Monitoring System Development Definition". Tech. rep., Ford Research Laboratory, 1996. Last modified April 18, 2002.

[100] PILUTTI, T., AND ULSOY, A. G. "Identification of Driver State for Lane-Keeping Tasks". *IEEE Transactions on Systems, Man and Cybernetics-Part A: Systems and Humans, Vol. 29*, No. 5 (September 1999), pp. 486–502.

[101] Popkin, S. "Effect of Day Length on Sleep Habits and Subjective On Duty Alertness in Irregular Work Schedules". In *82nd Annual Meeting of the Transportation Research Board* (Washington, DC, January 12-16 2003).

[102] Popkin, S. "The Operator Fatigue Management Program: A Multimodal Initiative for the Transportation Enterprise". In *Maritime Operations: Human Factors* (Linthicum Heights, MD, April 27 2004).

[103] Rajamani, R. *Vehicle Dynamics and Control.* Springer, 2006.

[104] Ramanata, P. "Optimal Vehicle Path Generator Using Optimization Methods". Master's thesis, Virginia Polytechnic Institute and State University, 1998.

[105] Reimpell, J., and Stoll, H. *The Automotive Chassis: Engineering Principles.* Society of Automotive Engineers, Inc., 1996.

[106] Renner, G., and Mehring, S. "Lane Departure and Drowsiness – Two Major Accident Causes - One Safety". In *The 4th World Congress on Intelligent Transport Systems* (Berlin, Germany, October 21-24 1997).

[107] Rimini-Doering, M., Manstetten, D., Altmueller, T., Ladstaetter, U., and Mahler, M. "Monitoring Driver Drowsiness and Stress in a Driving Simulator". Tech. rep., Corporate Research Division, Bosch, 2003.

[108] Roman, B., Pavel, S., Miroslav, P., Petr, V., and Lubomir, P. "Fatigue Indicators of Drowsy Drivers Based on Analysis of Physiological Signals". In *2nd International Symposium on Medical Data Analysis* (Madrid, Spain, 2001), pp. 62–68.

[109] Rosenthal, T. *STISIM Drive manual*, 2005.

[110] Royal, D. "Volume I: Findings, National Survey of Distracted and Drowsy Driving Attitudes and Behavior: 2002". Tech. Rep. DOT HS 809 566, The Gallup Organization, NHTSA, April 2003.

[111] ROYAL, D. "Volume III: Methods Reports, National Survey of Speeding and Unsafe Driving, And Distracted and Drowsy Driving Attitudes and Behavior: 2002". Tech. rep., The Gallup Organization, NHTSA, April 2003.

[112] RUSSELL, S., AND NORVIG, P. *Artificial Intelligence: A Modern Approach.* Prentice Hall, 2003.

[113] SAGBERG, F., JACKSON, P., KRUGER, H.-P., MUZET, A., AND WILLIAMS, A. "Fatigue, sleepiness and reduced alertness as risk factors in driving". Tech. Rep. TOI report 739/2004, The Institute of Transport Ergonomics, 2004.

[114] SALAH, K., AND MICHEL, V. "Drowsiness of the Driver: EEG and Vehicle Parameters Interaction". In *The fourteenth international technical conference on enhanced safety of vehicles* (Munich, Germany, 1994), pp. 443–461.

[115] SANDERS, M., AND MCCORMICK, E. *Human factors in engineering and design*, 7th edition ed. Science Serving Society, 1993.

[116] SEEING MACHINES. *faceLAB4 version 4.5*, 2007. www.seeingmachines.com/facelab.htm.

[117] SHERIDAN, T. *Humans and Automation.* John Wiley & Sons, 2002.

[118] SHERIDAN, T., AND FERRELL, W. *Man-Machine Systems: Information, Control, and Decision Models of Human Performance.* The MIT Press, 1981.

[119] SHERRY, P. "Fatigue Countermeasures in the Railroad industry: Past and Current Developments". Tech. rep., Intermodal Transportation Institute, University of Denver, 2000.

[120] SLEEPNET.COM. 2007. www.sleepnet.com.

[121] SPIEGEL, M. *Schaum's outline of theory and problems of statistics.* McGraw-Hill, 1999.

[122] STROHL, K. P. "Drowsy Driving and Automobile Crashes". Tech. Rep. DOT HS 808 707, NHTSA, US Department of Health and Human Service, April 1998.

[123] SWEATMAN, P., AND JOUBERT, P. "Detection of Changes in Automobiles Steering Sensitivity". *Human Factors, Vol. 16* (1974), pp. 29–36.

[124] SYSTEMS TECHNOLOGY, INC. . 2007. www.systemstech.com.

[125] TAO, G., AND KOKOTOVIC, P. *Adaptive Control of Systems with Actuator and Sensor Nonlinearities.* Wiley-Interscience, 1996.

[126] THE FEDERAL AVIATION ADMINISTRATION. 1995. www.hf.faa.gov.

[127] THIFFAULT, P., AND BERGERON, J. "Fatigue and individual differences in monotonous simulated driving". *Personality and Individual Differences, Vol. 34* (2003), pp. 159–176.

[128] THOMPSON, P., PARK, G., ALLEN, W., KLERMAN, E., THOMPSON, J., AND REED, G. "Sleep deprivation study for real time detection of human fatigue". Tech. Rep. 1363-1, Systems Technology, Inc., 2005.

[129] TIJERINA, L., GLECKLER, M., STOLTZFUS, D., JOHNSTON, S., GOODMAN, M., AND WIERWILLE, W. "A Preliminary Assessment of Algorithms for Drowsy and Inattentive Driver Detection on the Road". Tech. Rep. DOT HS 808, U.S. Department of Transportation NHTSA, 1999.

[130] TOKUTAKE, H., MIURA, Y., AND OKUBO, H. "Workload Analysis Method via Optimal Driver Model". Tech. Rep. SAE TECHNICAL 2004-01-3536, SAE International, 2004.

[131] TSANG, P., AND VIDULICH, M., Eds. *Principles and Practice of Aviation Psychology.* Lawrence Erlbaum Associates, 2003.

[132] UCHIYAMA, Y., EBE, K., KOZATO, A., OKADA, T., AND SADATO, N. "The neural substrates of driving at a safe distance: a functional MRI study". *Neuroscience Letters, Vol. 352* (2003), pp. 199–202.

[133] VAN DONGEN, H., AND DINGES, D. "Circadian Rhythms in Fatigue, Alertness and Performance". In *Principles and Practice of Sleep Medicine* (Philadelphia, PA), Elsevier, pp. 391–399.

[134] Van Dongen, H., and Dinges, D. "Investigating the interaction between the homeostatic and circadian processes of sleep-wake regulation for the prediction of waking neurobehavioural performance". *Journal of Sleep Research, Vol. 12* (2003), pp. 181–187.

[135] Van Dongen, H., Maislin, G., Mullington, J., and Dinges, D. "The Cumulative Cost of Additional Wakefulness; Does-Response Effects on Neurobehavioral Functions and Sleep Physiology From Chronic Sleep Restriction and Total Sleep Deprivation". *Sleep, Vol. 26* (2003), pp. 117–126.

[136] Wang, Q., Yang, J., Ren, M., and Zheng, Y. "Driver Fatigue Detection: A Survey". In *Proceedings of the 6th World Congress on Intelligent Control and Automation* (Dalian, China, June 21-23 2006).

[137] Washington State Department of Transportation. *www.wsdot.wa.gov/Projects/I90/TwoWayTransit/*, 2007.

[138] Weiskotten, T. "On the effects of the loss of sleep". *Journal of Experimental Psychology, Vol. 8* (1925), pp. 363–380.

[139] Weiskotten, T., and Ferguson, J. "A further study of the effects of loss of sleep". *Journal of Experimental Psychology, Vol. 13* (1930), pp. 247–266.

[140] Wickens, C., Gordon, S., and Liu, Y. *An Introduction to Human Factors Engineering.* Addison-Wesley Educational Publishers Inc., 1998.

[141] Wickens, C., and Holland, J. *Engineering Psychology and Human Performance.* Prentice Hall, 1999.

[142] Wierwille, W., Ellsworth, L., Wreggit, S., Fairbanks, R., and Kirn, C. "Research on vehicle based driver status-performance monitoring: development, validation and refinement of algorithms for detection of driver drowsiness". Tech. Rep. DOT HS 808 247, NHTSA, 1994.

[143] Wright, N., Stone, B., Horberry, T., and Reed, N. "A review of in-vehicle sleepiness detection devices". Tech. Rep. PPR 157, Transportation Research Laboratory, 2007.

[144] YANG, L. C. *Aircraft Conflict Analysis and Real-Time Conflict Probing Using Probabilistic Trajectory Modeling.* PhD thesis, Department of Aeronautics and Astronautics, MIT, 2000.

[145] YOUNG, R., HSIEH, L., GRAYDON, F., GENIK, R., BENTON, M., GREEN, C., BOWYER, S., MORAN, J., AND TEPLEY, N. "Mind-on-the-Drive: Real-Time Functional Neuroimaging of Cognitive Brain Mechanisms Underlying Driver Performance and Distraction". Tech. Rep. SAE TECHNICAL 2005-01-0436, SAE International, 2005.